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Modelling and Forecasting of Usd/Try Exchange Rate Using ARMA-GARCH Approach

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Abstract

Accurately predicting the exchange rate prices helps investors to obtain maximum profit from their exchange rate investments as well as to help firms conducting business with exchange rates to manage their trading based on these predictions. Therefore, the prediction of exchange rate prices is crucial for both investors and companies engaged in exchange rates. In this study, ARMA (Autoregressive Moving Average) models combined with various GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models are applied to model exchange rate prices. For this purpose, ARMA-GARCH (M) models are investigated in order to determine the effect of volatility on exchange rate prices as well as ARMA-GARCH models in which the errors are distributed both symmetrically and skewed. It is concluded that the best fitted model which is determined based on the goodness of fit and estimation accuracy performance criteria, is firstly ARMA-NAGARCH model which can model asymmetric and non-linear structures and secondly ARMA-GJRGARCH model. However, since the performance of ARMA-GARCH (M) models is lower than ARMA-GARCH models, the effect of volatility on exchange rate prices is found to be weak.

Keywords: ARIMA, GARCH Models, Exchange Rates, Forecasting, Model Evaluation

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ARMA-GARCH Yaklaşımı İle Usd/Try Döviz Kurunun Modellenmesi ve Tahmini

Özet

Döviz kuru fiyatlarının doğru bir şekilde tahmin edilmesi, yatırımcıların döviz kuru yatırımlarından maksimum kazanç elde etmelerine ve döviz kurları ile iş yapan firmaların bu tahminlere göre ticaretlerini yönetmelerine yardımcı olur. Bu nedenle döviz kuru fiyatlarının tahmini, hem yatırımcılar hem de döviz kurlarıyla iş yapan şirketler için çok önemlidir. Bu çalışmada, döviz kuru fiyatlarını modellemek için çeşitli GARCH (Genelleştirilmiş Otoregresif Koşullu Değişken Varyans) modelleri ile birleştirilmiş ARMA (Otoregresif Hareketli Ortalama) modelleri uygulanmıştır. Bu amaçla, volatilitenin döviz kuru fiyatları üzerindeki etkisini belirlemek için hataların hem simetrik hem de çarpık olarak dağıldığı ARMA-GARCH (M) modelleri ve ARMA-GARCH modelleri incelenmiştir. Uyum iyiliği ve tahmin doğruluğu performans kriterlerine göre belirlenen en uygun modelin, ilk olarak asimetrik ve doğrusal olmayan yapıları modelleyebilen ARMA-NAGARCH modeli ve ikinci olarak ise ARMA-GJRGARCH modeli olduğu sonucuna varılmıştır. Bununla birlikte ARMA-GARCH (M) modellerinin performansı, ARMA-GARCH modellerine göre daha düşük olması nedeniyle volatilitenin döviz kuru fiyatlarına etkisi zayıf bulunmuştur.

Anahtar Sözcükler: ARIMA, GARCH Modelleri, Döviz Kuru, Öngörü, Model Değerlendirme

1. Introduction

For the investors in the financial area to make maximum profit from their investments and to guide the trade of the firms doing business with the exchange rate, the exchange rate forecast is very important. In terms of that Investors in financial area make maximum profit from their investments and firms doing business with exchange rate govern their trade, the exchange rate forecast is fundamental. Accordingly, it is a critical process to determine the method which can accurately model exchange rate prices. For this purpose, many methods are used in the literature. For this purpose, a large number of methods are used in the literature. One of these methods is artificial neural networks based on artificial intelligence techniques (de Oliveira et al., 2013). Although this method gives very effective results in modelling nonlinear relationships, it does not possess an explicit functional form and thus it is difficult to conduct further analysis by means of this method. Other time series prediction methods commonly used are AR (Autoregressive), MA (Moving Average), ARMA (Autoregressive Moving Average) and ARIMA (Autoregressive Integrated Moving Average) introduced by Box et al. (1994). These methods are modelled with its lagged values, its lagged errors or their combinations. These methods are frequently utilized in time series modelling due to their functional form and high applicability through various computer programs. However, although these models can accurately model exchange rate prices, the issue of heteroscedasticity which is one of time series assumptions and occurs in non-stationary time series cannot be solved by this method and thus the predictions obtained from this model can be misleading. Heteroscedasticity problem encountered in the time series can be solved via ARCH (Autoregressive Conditional Heteroscedasticity) introduced by Engle (1982) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models developed by Bollerslev (1986). ARCH models are an effective tool in coping with the heteroscedasticity of time series. The disadvantage of this method is that it requires a high number of parameter estimates to model volatility, causing heavy computational load and loss of time. GARCH models are developed to handle the issue of a large number of parameter estimates in ARCH models and so GARCH models need less parameter estimations compared to ARCH models. On the other hand, ARCH models are modelled with only its lagged errors, while GARCH models are explained based on both lagged errors and lagged conditional variance and indicate stability in conditional variance. Agnolucci (2009) WTI compares the volatility forecast performance of these two models used by estimating the volatility of crude oil futures with GARCH type models and implied models. This study determines that there exist asymmetric effects in volatility of oil prices futures. Lim and Sek (2013) employ GARCH models to model volatilities in stock

markets in Malaysia. In the study, pre-crisis and post-crisis periods are considered separately and asymmetric GARCH models are more appropriate for the post-crisis period while symmetrical GARCH models performed better for pre-crisis period. It is also determined that exchange rates and oil prices have a significant impact on the volatility of the Malaysian stock markets. Studies via GARCH models are performed by Teresiene (2009), Efimova and Serletis (2014), Abdalla and Winker (2012) and Liu and Hung (2010). A hybrid method which is called ARMA-GARCH has been developed to model the conditional mean and conditional volatility of financial assets. This method overcomes the issue of heteroscedasticity in residuals obtained from the ARIMA model and thus produces more accurate forecasts. Mohammadi and Su (2010) use ARIMA-GARCH model to model the conditional mean and volatility of weekly crude oil spot prices in eleven international markets. It is concluded that APARCH model gives better results compared to other models and conditional standard deviation is better than conditional variance in catching the volatility of oil returns. Kang and Yoon (2013) investigate the means and volatilities of returns of the three oil types futures through various ARIMA-GARCH models. As a result of the out of sample performance analysis, it is concluded that a single model is not better than the others but that the ARFIMA-GARCH model is better able to capture the long-term memory of the returns and volatilities. Yaziz et al. (2013) employ hybrid ARIMA-GARCH model to forecast gold prices. This study demonstrates that this model is very effective in modeling nonlinear structures in the series and increases the performance of forecasting. Dritsaki (2017) investigates the returns of British pounds and the US dollar exchange rate using three types of ARMA-GARCH models and finds out that ARIMA-EGARCH model that is distributed Student t is the best in modeling the return and volatility of the related exchange rate. Gupta and Kashap (2016) models and forecasts the INR/GBP exchange rate via the hybrid ANN-GARCH approach. Atabani Adi (2019) models RMB/USD exchange rate return volatility using GARCH-type approaches. Epaphra (2016) employs the GARCH and EGARCH methods to model TZS/USD exchange rate volatility. Caporale and Zekokh (2019) investigate the volatility of cryptocurrencies through Markov-Switching GARCH models. Abdullah et al. (2017) models and forecasts the USD/BDT exchange rate using GARCH models where errors are normal and Student t distributed. They also compare the performances of the models used. Pahlavani and Roshan (2015) use ARIMA and hybrid ARIMA-GARCH models to forecast the IRR/USD exchange rate. It then compares the performances of the models used.

This paper aims to investigate the USD/TRY exchange rates in a wide perspective by using ARIMA-GARCH models. It tries to determine the most fitted model by assuming different distributions of errors and also analyzes the effect of volatility on USD / TRY exchange rate prices. For this purpose, the model that forecasts the best exchange rate is estimated via different ARMA-GARCH models. The best fitted model selection is performed using both goodness of fits based on all sample and the measures of out of sample performance and thus more accurate forecast model is chosen in this way. On the other hand, the exchange rate prices are better modelled by approaching with both asymmetric and nonlinear models and the model selection is made with more accurate prediction results.

The rest of the paper is designed as follows. Section 2 describes the ARMA-GARCH methodology and its different types. Section 3 presents model adequacy and the performance measures of forecast accuracy used in the study. Section 4 gives the experimental results obtained from the study. Finally, Section 5 includes the conclusion which summarizes the contribution and important results of the paper.

2. ARIMA-GARCH Models

ARIMA (Autoregressive Combined Moving Average) models Introduced by Box and Jenkins (1976) are time series forecasting methods commonly used in many areas, especially statistics. This method produces forecasts based on the autocorrelation structure in the time series and is defined as follows:

$$y_t = \mu + \sum_{i=1}^p \varphi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (1)$$

Here, μ , φ_i and θ_j are constant term, i th autoregressive coefficient and j th moving average coefficient respectively and ε_t is error term at t time. Moreover, p and q represent autoregressive and moving average term order in turn. Modeling the time series via ARIMA method is performed in four stages. First, the model structure is determined by the autocorrelation (ACF) and partial autocorrelation (PACF) functions which are informative on the characteristic structure of the time series. Second, model parameters can be estimated by the maximum likelihood method. In the third stage, it is checked whether residuals obtained from the estimated model is a white noise process. Finally, future values are forecasted by means of estimated model. It is noted that longer forecast period is, less accurate the forecast is. In traditional ARIMA models error term ε_t should be zero mean and homoscedasticity as well as uncorrelated. When the time series exhibit the conditional heteroscedasticity, the application of ARCH models proposed by Engle (1982) provides more accurate forecast values. ARCH models deal with the serial correlation in time-varying volatility. However, the model does not produce effective results when it is necessary to estimate a large number of parameters in ARCH models. Bollerslev (1986) developed GARCH (Generalized Autoregressive Conditional Variable Variance) models which are generalizations of ARCH models. In this model, conditional variance takes into account not only the lagged errors but also the value of the lagged conditional variance. The general structure of the GARCH model is defined as follows:

$$\varepsilon_t = \sigma_t z_t \quad (2)$$

$$\sigma_t = \alpha + \sum_{i=1}^m \beta_i \sigma_{t-i}^2 + \sum_{j=1}^n \delta_j \varepsilon_{t-j}^2 \quad (3)$$

Where, α , β_i and δ_j are described as a constant term, i th GARCH parameter and j th ARCH parameter, respectively and these parameters are non-negative values. In the GARCH model given in Eq. (3), the effect of the ε_t shocks is symmetric. That is, positive shocks with the same magnitude negative shocks have the same effect on volatility. The ARIMA-GARCH approach has been developed to handle the serial correlated residuals encountered in ARIMA models. This model allows the modeling of both the conditional means and the volatility of the series. In addition, this approach provides more accurate forecast values and higher forecast performance compared to ARIMA models. There are many types of GARCH models in the literature. Investigation extensively for the most fitted model among these models and determination of the best suitable GARCH model are crucial process in the time series forecasting. Some of the GARCH models can model symmetric time-varying volatility while others model asymmetric volatility and leverage. By investigating comprehensively GARCH models, the features of the time series can be determined more accurately.

Alternative GARCH models are Threshold GARCH (TGARCH) (Zakoian, 1994), Glosten-Jagannathan-Runkle GARCH (GJRARCH) (Glosten et. Al., 1993), Exponential GARCH (EGARCH) (Nelson, 1991) and Nonlinear Asymmetric GARCH (NAGARCH) (Engle and Ng, 1993). These models are able to capture asymmetric structures and leverage that the standard GARCH model cannot capture. For instance, consider the GJRARCH model developed by Glosten et al. (1993):

$$\sigma_t = \alpha + \sum_{i=1}^m \beta_i \sigma_{t-i}^2 + \sum_{j=1}^n \delta_j \varepsilon_{t-j}^2 + \sum_{j=1}^n \gamma_j \varepsilon_{t-j}^2 I_{t-j} \quad (4)$$

Here, I_{t-j} is a indicator function and is described as follows:

$$I_{t-j} = \begin{cases} 0, & \varepsilon_{t-j} \geq 0 \\ 1, & \varepsilon_{t-j} < 0 \end{cases} \quad (5)$$

GJRARCH model can also model asymmetric effects. If $\gamma_j > 0$ there is a leverage effect. That is, it means that the effect of negative shocks ($\delta_j + \gamma_j$) in modeling volatility it is greater than the effect of positive shocks (δ_j). The NAGARCH model, which can model asymmetric and nonlinear effects, can be defined as follows:

$$\sigma_t = \alpha + \sum_{i=1}^m \beta_i \sigma_{t-i}^2 + \sum_{j=1}^n \delta_j (\varepsilon_{t-j} - \gamma_j \sigma_{t-j})^2 \quad (6)$$

In this paper, the effect of conditional volatility of exchange rate on the average of exchange rate with GARCH-in-mean (GARCH-M) models is also investigated.

In order to determine the effect of conditional volatility on GARCH (M) models, the term of conditional heteroscedasticity is added to mean equation. For example, the mean equation with the GJRGARCH model defined in Eq. (4) can be written as follows:

$$y_t = \mu + \sum_{i=1}^p \varphi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \eta \sigma_t + \varepsilon_t \quad (7)$$

Here, η is a parameter that measures the effect of volatility on the mean of the time series. η parameter which is statistically significant η means that volatility has a substantial effect in explaining the behavior of exchange rate.

3. Model Sufficiency and Accuracy of Prediction

3.1. Evaluation of model sufficiency

Accuracy of model sufficiency is evaluated in two part. In the first part, goodness of fit measures calculated based on all sample are investigated. This measures are AIC (Akaike, 1973) and BIC (Schwarz, 1978) and these are evaluated according to log likelihood. The model that has the smallest AIC and BIC values is determined to be best fitted model to data. In the second stage, assumptions related to residuals from estimated model are tested. To this end, both autocorrelation (ACF) and partial autocorrelation (PACF) functions are investigated and autocorrelation tests such as Ljung-Box are applied to the residuals.

3.2. Evaluation of accuracy of prediction

Evaluating the performance of prediction accuracy also contribute to select the best model for the data along with goodness of fit measures. Prediction accuracies of various model used are analyzed via these measures. In this paper, four performance measures are utilized and these are mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and Theil's inequality coefficient (TIC). Prediction performance measures are calculated as follows:

$$\text{Mean absolute error (MAE)} = \frac{\sum_{t=1}^T |e_t|}{T}$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{e_t^2}{T}}$$

$$\text{Mean absolute percentage error (MAPE)} = \frac{\sum_{t=1}^T \frac{e_t}{y_t}}{T}$$

$$\text{Theil's inequality coefficient (TIC)} = \frac{\sqrt{\frac{e_t^2}{T}}}{\sqrt{\frac{1}{T} \sum_{t=1}^T y_t^2} + \sqrt{\frac{1}{T} \sum_{t=1}^T \hat{y}_t^2}}$$

Where, $e_t = y_t - \hat{y}_t$ and T represents length of test data. mean absolute error (MAE) and root mean square error (RMSE) are sensitive to the scale of variables. That is, they should be used to measure performances of the same variable in different models. On the other hand, mean absolute percentage error and Theil's inequality coefficient

don't depend on variable's scale and thus they are commonly utilized for both the same variable and different variables. The models with smallest prediction errors are indicated as the best fitted model.

4. Empirical Findings

4.1. Data description

In this study, daily USD/TRY exchange rate is used. The data set consists of 746 observations ranging from 01/01/2016 to 31/12/2018 and is demonstrated in Fig. 1. To evaluate the accuracy of the estimation, data set is divided into two parts: training data and test data. The training data comprises of 597 observations and this includes approximately 80 percent of all data. The remaining is considered as test data and consists of 149 data.

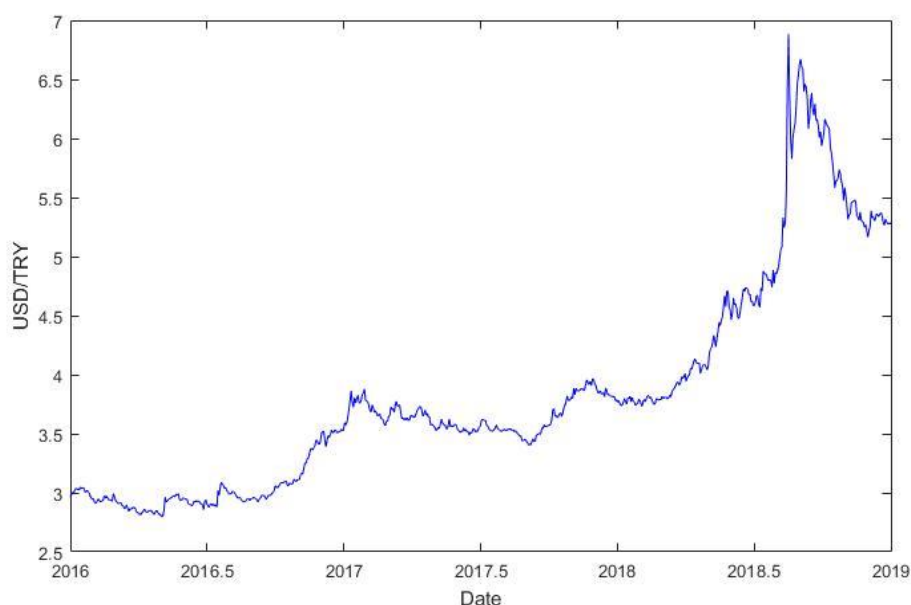


Figure 1: Observed Values of USD/TRY

When viewed Fig. 1, USD / TRY exchange rate has generally an upward trend and this suggests that the series have nonstationary features. However, it exhibits more volatile progress since 2017 while there is an almost constant price movement throughout 2016. The exchange rate reaches the peak point in the second half of 2018 and this period is considered as breaking period for Turkey's economy. After this period, the USD/TRY exchange rate begins quickly to decline and the Turkey's economy gradually moves to normalization period.

Table 1: Descriptive statistics for USD/TRY exchange rate

Statistics	Value
Mean	3.8334
Median	3.6253
Std. Dev.	0.9071
Min.	2.7955
Max.	6.8834
Skewness	1.2580
Kurtosis	0.9362
Observations	746

Descriptive statistics belonging to the USD/TRY exchange rate are presented in Table 1. According to this table, USD/TRY exchange rates show more right skewed and excess kurtosis distribution than normal distribution. This

indicates that the exchange rate is not normally distributed. Therefore, Student t and skewed Student t distributions are investigated in time series forecasting models used in the study. A research in broad perspective is carried out for ARMA-GARCH models that can model the exchange rate. While the standard GARCH model can model the symmetrical effects in volatility, alternative GARCH models can model asymmetric effects over time in volatility. For this reason, including alternative GARCH models to the study leads to obtain more accurate results.

Table 2: Evaluation of goodness of fit for ARMA-GARCH models

Model	AIC	BIC
EGARCH-ST	-6.6068	-6.5387
EGARCH-ST-M	-6.6031	-6.5288
EGARCH-T	-6.6128	-6.5509
EGARCH-T-M	-6.5953	-6.5271
GJR-ST	-6.5997	-6.5316
GJR-ST-M	-6.5991	-6.531
GJR-T	-6.6012	-6.5293
GJR-T-M	-6.5916	-6.5334
NAGARCH-ST	-6.6224	-6.5543
NAGARCH-ST-M	-6.6198	-6.5454
NAGARCH-T	-6.609	-6.5471
NAGARCH-T-M	-6.6018	-6.5336
NGARCH-ST	-6.6108	-6.5427
NGARCH-T	-6.6066	-6.5446
SGARCH-ST	-6.5991	-6.5371
SGARCH-ST-M	-6.5964	-6.5283
SGARCH-T	-6.5916	-6.5358
SGARCH-T-M	-6.5913	-6.5293
TGARCH-ST	-6.6153	-6.5471
TGARCH-ST-M	-6.6111	-6.5368
TGARCH-T	-6.6046	-6.5427
TGARCH-T-M	-6.602	-6.5338

However, volatility can also have an impact on USD/TRY exchange rates. ARMA-GARCH (M) models developed for this purpose are analysed in the study and this paper is assessed in very broad manner. Finally, since skewed distributions can model some financial variables better than non-skew distributions, the distribution of errors is assumed to be Student t and skewed Student t distribution. In order to select the model that can best model the exchange rate, goodness of fit measures based on whole data set and performance measures of forecasting accuracy calculated based on the test data are utilized. The model with the smallest value according to the AIC and BIC criteria calculated by regarding the number of parameters used in the model is selected as the best model. Goodness of fit measures for the models is presented in Table 2. When the best fitted model according to AIC values is investigated, the ARMA-NAGARCH model, in which the errors are skewed Student t distributed, is determined as the best model and ARMA NAGARCH (M) model, in which the errors are skewed Student t distributed, is an alternative model to ARMA-NAGARCH model. It is found that GARCH model in which the errors are Student t distributed was the worst model. According to the BIC information criterion, the best fitted model is ARMA-NAGARCH model in which errors are skewed Student t distributed and this model is followed by ARMA-EGARCH model in which errors are Student t distributed. It is selected that the poor model is ARMA-EGARCH (M) where errors are Student t distributed. On the other hand, in this paper the mean absolute error, the square root of the error squared, mean absolute percentage error and Theil's inequality coefficient are used as measures of forecasting performance for the best fitted model selection. The results obtained according to the performance criteria of forecasting accuracy are demonstrated in Table 3.

Table 3: Evaluation of model forecasting performance for ARMA-GARCH models

Model	MAE	RMSE	MAPE	TIC
EGARCH-ST	0.07651	0.129	1.36327	0.02373
EGARCH-ST-M	0.07525	0.12821	1.33816	0.02358
EGARCH-T	0.07727	0.13003	1.37276	0.02391
EGARCH-T-M	0.07715	0.13	1.37083	0.02391
GJR-ST	0.0751	0.12776	1.33461	0.0235
GJR-ST-M	0.07605	0.12869	1.35364	0.02367
GJR-T	0.07637	0.12748	1.35813	0.02345
GJR-T-M	0.07528	0.12811	1.33873	0.02357
NAGARCH-ST	0.07623	0.12876	1.35482	0.02368
NAGARCH-ST-M	0.08236	0.13483	1.46122	0.02478
NAGARCH-T	0.07645	0.12879	1.35876	0.02368
NAGARCH-T-M	0.07687	0.12983	1.36631	0.02388
NGARCH-ST	0.07741	0.13065	1.37794	0.02403
NGARCH-T	0.07638	0.12971	1.35694	0.02385
SGARCH-ST	0.07634	0.12941	1.35871	0.0238
SGARCH-ST-M	0.0754	0.12863	1.34151	0.02366
SGARCH-T	0.07521	0.1283	1.33572	0.0236
SGARCH-T-M	0.07575	0.12883	1.34736	0.0237
TGARCH-ST	0.07589	0.12909	1.34928	0.02374
TGARCH-ST-M	0.07502	0.12784	1.3356	0.02351
TGARCH-T	0.07542	0.12813	1.33927	0.02357
TGARCH-T-M	0.07525	0.12781	1.33802	0.02351

The ARMA-TGARCH (M) model is the most appropriate model in which the errors are skewed Student t distributed in terms of the mean absolute error value according to the value of mean absolute error value from performance measure of forecasting accuracy used and then the ARMA-TGARCH model in which the errors are skewed Student t distributed follows this model. The worst model is ARMA-NAGARCH (M) in which errors are skewed Student t distributed. According to other performance evaluation criteria, the most compatible models are RMSE, MAPE and TIC ARMA-GJRGARCH model where errors are Student's distributed, ARMA-GJRGARCH model where errors are skewed Student, and ARMA-GJRGARCH models where errors are distributed. When similar evaluations are performed according to other performance evaluation criteria such as RMSE, MAPE and TIC, the best fitted models are ARMA-GJRGARCH with Student t errors, and ARMA-GJRGARCH with skewed Student t errors, and ARMA-GJRGARCH with Student t errors, respectively. The model that possesses the worst performance is ARMA-NAGARCH (M) in which errors are skewed Student t distributed in terms of RMSE, MAPE and TIC measures. There is no single result for the best model when both the goodness of model fit criteria and the performance criteria of forecasting accuracy are taken into account. However, ARMA-NAGARCH model in which errors are skewed Student t distributed can be regarded as the most fitted model according to AIC and BIC models. GJRGARCH model with Student t errors can be taken into account as alternative to the best fitted model in terms of performance criteria of estimation accuracy and the most compatible model is Student's GJRGARCH model. The values of estimates obtained from two candidate models are shown in Fig. 2 and Fig. 3.

Table 4: Parameter estimates of mean equations for the best fitted models

	μ	φ_1	φ_2	θ_1	θ_2
NAGARCH	0.0007 (0.0001)	-0.7677 (0.0059)	-0.9874 (0.0020)	0.7692 (0.0013)	1.0040 (0.0003)
GJRGARCH	0.0001 (0.0002)	-0.4387 (0.3213)	0.4637 (0.2976)	0.3943 (0.3162)	-0.4797 (0.2857)

In the stage of the best fitted model selection, it is found out that conventional ARMA-GARCH model gives poor results compared to alternative GARCH models in modelling the USD/TRY exchange rate. This may be due to the fact that the GARCH model can only capture symmetrical effects. However, considering the most suitable models, it is discovered that USD/TRY exchange rate has the leverage effect and an asymmetric effect that is thought as common feature of financial assets. In addition, it is found that non-linear models have better results in modelling exchange rates. However, it is determined that the proposed ARMA-GARCH models increased the forecasting accuracy performance by approximately 5 % to 8 %.

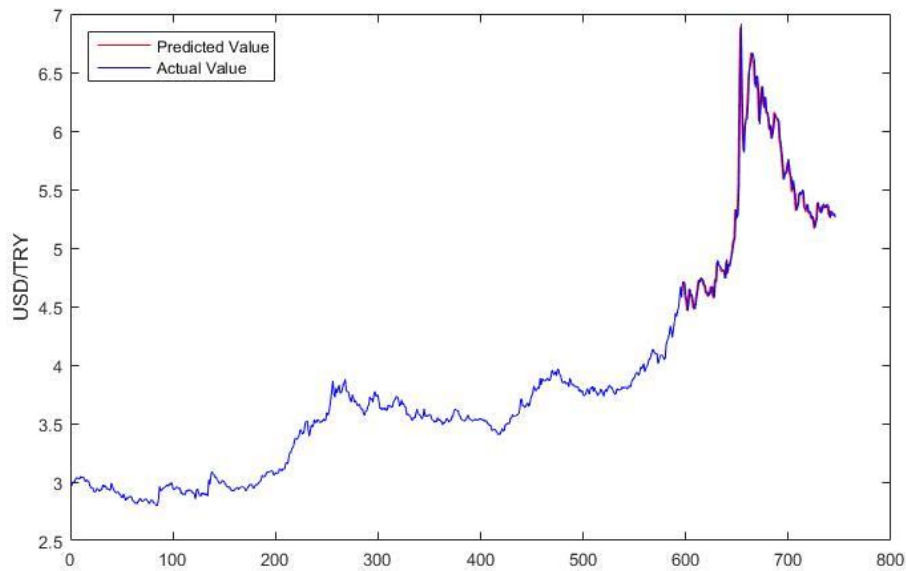


Figure 2: Actual and predicted values for ARMA-NAGARCH

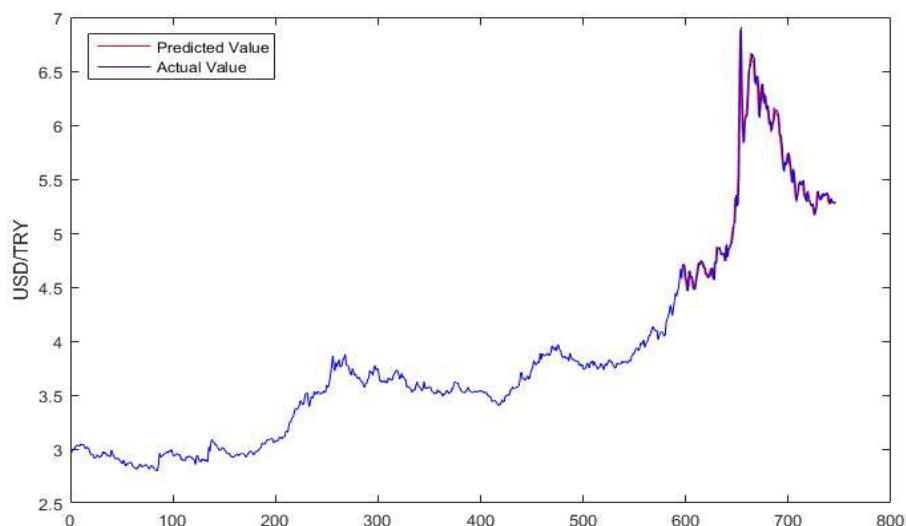


Figure 3: Actual and predicted values for ARMA-GJRGARCH

Table 5: Parameter estimates of variance equations for the best fitted models

	α	δ	β	η	ν	λ
NAGARCH	0.0000 (0.0000)	0.0076 (0.0000)	0.5691 (0.0024)	-7.3366 (0.0252)	4.9695 (0.6547)	1.2021 (0.0589)
GJRGARCH	0.0000 (0.0000)	0.1547 (0.0405)	0.8427 (0.0356)	-0.0688 (0.0536)	4.8944 (0.9304)	

* Values in parenthesis show the standard error of the estimated parameters

Parameter estimates of the best fitted ARMA-GARCH models are presented in Table 4 and Table 5. All parameter results are tested 5% significance level and it is found that almost all parameters are statistically significant. This indicates that the price of the exchange rate has a changing volatility changing over time. However, NAGARCH model, which is determined as the best fitted model, can model asymmetric and nonlinear structure in volatility and it implies that volatility of the exchange rate has a time varying asymmetric and nonlinear effect. The fact that skewed Student t distribution for errors is statistically significant indicates that skewed distributions are better than non-skewed distributions in modelling the exchange rates. Both ARMA-NAGARCH and ARMA-GJRGARCH model have persistence in volatility over time. In both models, the effects of lagged conditional variance are rather higher than the effect of lagged errors.

Table 6: Results of autocorrelation test for residuals from best fitted ARMA-GARCH models

	$Q(10)$ stat	$Q^2(10)$ stat	$Q(20)$ stat	$Q^2(20)$ stat
ARMA-NAGARCH	6.2789 (0.7913)	14.193 (0.1644)	16.034 (0.7145)	29.346 (0.08116)
ARMA-GJRGARCH	4.5341 (0.9201)	7.9025 (0.6384)	14.479 (0.8054)	20.244 (0.4427)

It is investigated whether residuals from the best fitted ARMA-GARCH model exhibit autocorrelation by means of Ljung-Box test and results are presented in Table 6. It is found that residuals from the best appropriate models are identically and independently distributed such as white noise. This means that estimated models are suitable for modelling USD/TRY exchange rate. ACF and PACF of these residuals are demonstrated between Fig. 4 and Fig 5. and these also indicates that the residuals are white noise. On the whole, it is found out that the exchange rate has an asymmetric and non-linear effect and alternative ARMA-GARCH models such as NAGARCH and GJRGARCH are effective tool in modelling these feature.

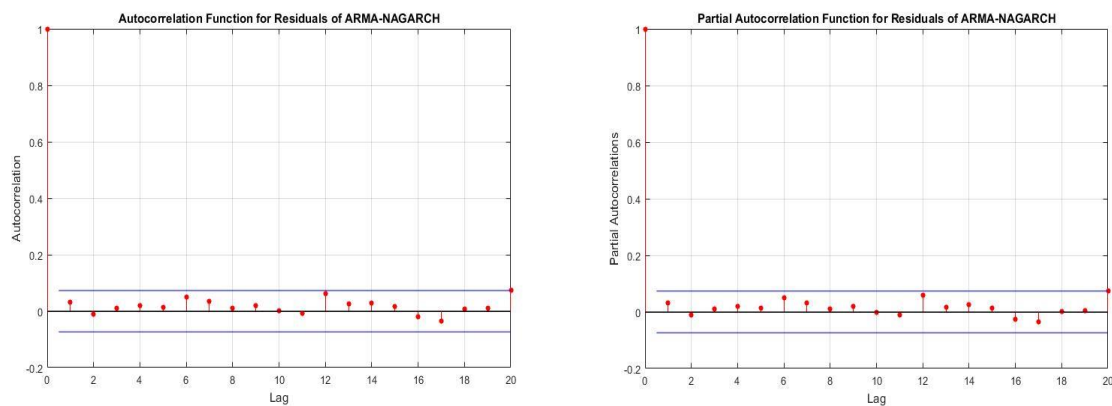


Figure 4: Autocorrelation and partial autocorrelation functions for residuals from ARMA-NAGARCH models

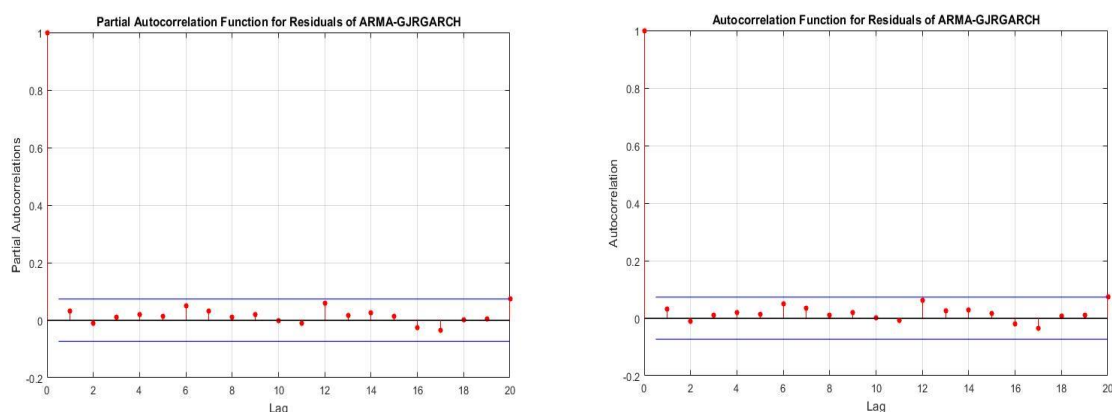


Figure 5: Autocorrelation and partial autocorrelation functions for residuals from ARMA-GJRGARCH models

5. Conclusion

Depending on the exchange rate forecasting values, the investors make a plan to make the maximum profit from their exchange rate investments, and the firms that do business with the exchange rate direct their trade based on these forecasts. Therefore, the forecasts of exchange rate prices are crucial for both investors and companies engaged in exchange rates. It is a critical process to determine the method that can accurately model behaviours of exchange rates. The most important contribution of this study is that it includes a comprehensive model determination process by using a wide range of methods to model exchange rate prices. ARMA-GARCH and ARIMA-GARCH (M) models are used to model exchange rate prices and this includes many models. Model selection is performed based on both goodness of fit measures and performance measures of forecasting accuracy. Empirical results suggest that ARMA-GARCH models are more effective than ARMA-GARCH (M) in modelling USD/TRY exchange rate. Moreover, it is found that alternative ARMA-GARCH models which can model asymmetric and nonlinear effects give better results than conventional ARMA-GARCH model which can model only symmetric effects. It is determined that ARMA-NAGARCH in which errors are skewed Student t distributed can model the UST/TRY exchange rate and it is followed by ARMA-GJRGARCH with Student t errors. It implies that fitting only symmetric distribution in modelling exchange rate can give misleading results. In this paper, the prices of exchange rate are modelled based on its lagged values. However, the exchange rate depends on other variables such as inflation rate and terms of trade. In future studies, exchange rate is investigated by adding variables stated above as exogenous variables to the model.

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Actuaries Climate Index: An Application for Turkey

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Abstract

The aim of this paper is to propose a Turkish application of the Actuaries Climate Index (ACI), which is a measure of changes in extreme weather and sea levels. The index periodically provides data and information to scientists, practitioners and policy makers working with the risks caused by climate change in order to help them analyze the financial effects of these risks. For this aim, we calculate ACI for Ankara province using data obtained from standard databases. When the application suggested in this article is extended to the entire country, the recommended calculation will help the involvement of Turkey in addition to all European countries included in the European ACI, which is the continuation of the ACIs developed primarily in Canada and the USA.

Keywords: Climate Change, Extreme Weather Risks, Threshold, Reference Period, Standardized Anomaly, Sustainability

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Aktüerler İklim Endeksi: Türkiye için Bir Uygulama

Özet

Bu makalenin amacı, ekstrem hava ve deniz seviyesi değişikliklerinin bir ölçüsü olan Aktüerler İklim İndeksinin (AİE) için bir Türkiye uygulamasını önermektir. Endeks, iklim değişikliğinin neden olduğu risklerle çalışan bilim insanlarına, uygulayıcılara ve politika yapıcılara, bu risklerin finansal etkilerini analiz etmelerinde yardımcı olmak için periyodik olarak veri ve bilgi sağlamaktadır. Bu amaçla, standart veri tabanlarından elde edilen verileri kullanarak Ankara ili için AİE hesaplanmıştır. Bu makalede önerilen uygulama tüm ülke kapsamına genişletildiğinde, önerilen hesaplama ilk olarak Kanada’da ve ABD’de geliştirilen AİE’lerinin devamı olan Avrupa AİE’de yer alan tüm Avrupa ülkelerine ek olarak Türkiye’nin de dahil olmasına yardımcı olacaktır.

Anahtar Sözcükler: Ekstrem Hava Riskleri, Eşik Değer, İklim Değişikliği, Referans Periyodu, Standartlaştırılmış Anomali, Sürdürülebilirlik

1. Introduction

Global climate change has emerged in recent years as one of the most challenging issues confronting human society. The “Climate Action” target, one of Sustainable Development Goals (SDGs), adopted by United Nations, aims to strengthen resilience and ability for adaptation to hazards and natural disasters caused by climate change. As the amount of greenhouse gases produced by human activity rises, they accumulate in the atmosphere, warm the climate, and cause various changes in the atmosphere, on land, and in the oceans. According to the Greenhouse Gas Emission Statistics of the Turkish Statistical Institute; energy-related emissions has the largest share in total greenhouse gas emissions as CO₂ equivalent with 72%, followed by agriculture with 13.4%, industrial processes and product use with 11.2%, and waste sector with 3.4% in 2019 in Turkey. Energy sector emissions increased by 161% in 2019 compared to 1990 and amounted to 364.4 Mt CO₂ eq. whereas industrial processes and product use emissions increased by 147.1%. In addition, agricultural sector emissions increased by 47.7% and waste emissions by 55.7% in 2019 compared to 1990. The change in the pattern and severity of weather events negatively affects sustainable production conditions, and numerous business lines lose their attractiveness and have negative effects on the supply-demand balance. New risk management and insurance solutions are therefore required in consideration of this reality.

Various climate factors that represent extreme weather are used to generate the ACI. The Turkish Actuaries Climate Index (TrACI) seeks to offer data and information to insurance products that provide coverage against risks caused by climate change and to develop a benchmark that examines the financial consequences of these risks. This paper has a significant impact on economic and national energy security in addition to the strategic importance of climate change in actuarial operations such as risk management, product development, pricing, reserving, and investment decisions in the insurance sector. In this regard, developing a climate index unique to Turkey will fill a gap in the Turkish insurance market, especially for actuarial work based on environmental risks. Sustaining this index and providing regular updates will also contribute to the insurance industry.

As in many other disciplines, indices, which are functions that combine multiple indicators, are very useful in actuarial sciences. Indices are efficient since they are statistically robust and easy to understand. In this paper, it is aimed to develop ACI for Ankara by using standardized data sets in existing data sources. The ACI investigates changes in the frequency and length (i.e. severity) of extreme temperatures (high and low temperatures, separately), as well as the changes in heavy precipitation, drought, strong winds, and sea level.

2. Literature

The ACI was launched after a joint research project funded by four North American actuarial organizations that are the American Academy of Actuaries (AAA), the Canadian Institute of Actuaries (CIA), the Casualty Actuarial Society (CAS), and the Society of Actuaries (SOA) in 12 sub-regions in the US and Canada. Actuaries develop models to examine the consequences of uncertain climatic events on the financial losses of various businesses, just as climatologists, environmentalists, and agricultural scientists do in order to assess potential climate changes and their impacts on the environment and agriculture. As a result, the ACI might offer actuaries trustworthy data on “extreme” weather events, which is crucial for calculating and simulating insurance and financial risks associated with climate change (Pan et al., 2022).

Curry (2015) evaluates the ACI, which was initially developed over Canada and the United States, in light of the possibility of expanding it to include the United Kingdom and Europe. Reviewing the definition and underlying methodology of the ACI, it is concluded that no modifications are required for the UK-European ACI to be applied to the new domain. In 2018, the North American ACI was served as a model for the Australian ACI (AACI), as well (AACI, 2018). Kotnala et al. (2018) prepare a plan for creating a climate index for actuarial practice in India, which is called Indian ACI (IACI), after following the discussion of the efforts made by other groups, such as actuarial associations. Although these indices are developed with a similar goal, different underlying components of these ACI indices prevent direct comparison.

The insurance business has acknowledged that human health, mortality, and morbidity are also tied to climate change, in addition to property losses caused by natural disasters. Miljkovic et al. (2018) econometrically show the causality between property damages and mortality rates once the relationship between property damages and climate variables is established. Although there is a close relationship between index insurance and probabilistic seasonal predictions, Carriquiry and Osgood (2012) proposes to formalize this relationship for the first time in the literature by addressing interactions between insurance, climate forecast, and input decisions.

Moreover, Jiang and Weng (2019) focuses on the subject of climate change risk in the stock market by employing the ACI as a proxy for climate change risk. It is obtained that the ACI trends as a type of production risk have an adverse influence on agricultural productivity and corporate profitability of businesses involved in agriculture whereas a considerable forecasting power of climate change is discovered on company revenues.

Pan et al. (2022) investigate the effectiveness of the ACI and suggest a method that combines linear regression and probit regression models to evaluate and forecast agricultural losses for crop insurance and reinsurance applications.

3. The ACI Model

Advanced global climate models are utilized to predict how these indicators may change over time. The trend in public and structured data focuses on “average” changes over a given period. Instead of average climate change, the data sets used to develop the ACI are considered to assess the “risk” posed by climate change, which denotes the “frequency of severe climate changes”.

The assessment of climate change using the ACI is retrospective. The United States and Canada ACI measure, on which our study is based, incorporates data from 6 different climate indicators (ACI, 2018) given in Table 1.

Table 1. Definition of the ACI indicators

Indicator	Abbreviation	Definition
High temperatures	<i>T90</i>	Temperature frequencies above the 90th percentile
Low temperatures	<i>T10</i>	Temperature frequencies below the 10th percentile
Heavy rainfall	<i>P</i>	Maximum monthly rainfall for five consecutive days
Drought	<i>D</i>	Maximum consecutive dry days in a year
High wind	<i>W</i>	Wind speed frequencies above the 90th percentile
Sea level	<i>S</i>	Changes in sea level

3.1. The Calculation of Standardized Anomalies of ACI Components

The difference between a quantity and its average value throughout a reference period, divided by the quantity's standard deviation over the reference period, is the standardized anomaly (Curry, 2015).

The change in the frequency of warmer temperatures above the 90th percentile (*T90*) and colder temperatures below the 10th percentile (*T10*), relative to the reference period, are referred as the extreme temperature components. Since *T10* is often lower than it was during the reference period due to the recent warming of temperatures, the sign of *T10* is inverted in the calculation of the ACI in order to reflect its contribution to increased risk in the temperature distribution accurately. The melting of ice, the spread of diseases, and the population of pests and insects that were previously less likely to live at colder temperatures all contribute to a rise in the ACI's value as a result of the decrease of cold extremes.

In particular, the monthly frequency of daily maximum (i.e., often daytime) and minimum (i.e., typically nighttime) temperatures that fall below the 10th and above the 90th percentiles of the probability density function are used. These components, which are determined for the reference period, are summarized in Table 2 more specifically.

Table 2. Explanation of the frequencies of extreme surface temperatures

Notation	Explanation
TX90	The number of days above the 90th percentile of high temperatures
TX10	The number of days below the 10th percentile of high temperatures
TN90	The number of days above the 90th percentile of low temperatures
TN10	The number of days below the 10th percentile of low temperatures

The variations in exceedance frequency, or anomalies, are calculated as the difference between the exceedance frequency ($TX90$) and the mean of the exceedance frequencies of the related component determined across the monthly reference period, $\mu_{ref}(TX90)$. In addition, the standardized anomaly accurately determines how much of the variation is significant relative to the underlying degree of variability for each quantity, that is calculated by $\sigma_{ref}(TX90)$.

On the other hand, the correlation between warm/cold days and nights must be taken into consideration. In order to prevent the temperature components of the ACI from being over-weighted, the average of warmer (colder) days and warmer (colder) nights are used. Therefore, the following equations appear to be the standardized anomaly of high and low temperatures, respectively.

$$T90_{std} = \frac{1}{2} \left(\frac{TX90 - \mu_{ref}(TX90)}{\sigma_{ref}(TX90)} + \frac{TN90 - \mu_{ref}(TN90)}{\sigma_{ref}(TN90)} \right) \quad (1)$$

$$T10_{std} = \frac{1}{2} \left(\frac{TX10 - \mu_{ref}(TX10)}{\sigma_{ref}(TX10)} + \frac{TN10 - \mu_{ref}(TN10)}{\sigma_{ref}(TN10)} \right) \quad (2)$$

The highest 5-day rainfall ($Rx5day$) in the month, which measures flood risk (P), and the highest number of consecutive dry days (CDD) in a year with less than 1mm of daily precipitation, which measures drought (D), are the components of precipitation. Similar to how it is done for each of the other components, differences between the 5-day rainfall maxima and the number of consecutive dry days and their corresponding average values during the reference period are calculated for each month.

As the first component of precipitation, $Rx5day$ is the maximum of 5 consecutive days of precipitation in the relevant month, i.e. $Rx5day = \max(R_i)$ where R_i is calculated with the following formula.

$$R_i = \begin{cases} r_i + r_{i+1} + r_{i+2} + r_{i+3} + r_{i+4} & ; i = 1 \\ r_{i-1} + r_i + r_{i+1} + r_{i+2} + r_{i+3} & ; i = 2 \\ r_{i-2} + r_{i-1} + r_i + r_{i+1} + r_{i+2} & ; 2 < i \leq n - 2 \end{cases} \quad (3)$$

Here, r_i ; $i = 1, 2, \dots, n$ is the precipitation amount of the i^{th} day where n is the number of days in the relevant month.

As the second component of precipitation, the maximum number of consecutive dry days in a year, or $CDD(k)$, is used to determine the severity of a drought. Since the number of consecutive dry days per year could only be calculated as one value per year, unlike the temperature and rainfall components of the ACI, monthly values are obtained by a linear interpolation technique. Dry days are defined as those with less than 1 millimeter of precipitation. By using linear interpolation, as shown in the following equation, monthly values are derived for each month j , year k (ACI, 2018).

$$CDD(j, k) = \begin{cases} \frac{(12-j)}{12} CDD(12, k-1) + \frac{j}{12} CDD(12, k); j = 1, 2, \dots, 11 \\ CDD(k); j = 12 \end{cases} \quad (4)$$

Hence, the standardized anomaly of the monthly highest 5-day rainfall and monthly highest number of consecutive dry days are given in Equation (5) and (6), respectively.

$$P_{std} = \frac{Rx5day - \mu_{ref}(Rx5day)}{\sigma_{ref}(Rx5day)} \quad (5)$$

$$D_{std} = \frac{CDD - \mu_{ref}(CDD)}{\sigma_{ref}(CDD)} \quad (6)$$

In addition to the temperature and precipitation components, wind power component is also included in the ACI. Using the formula $WP = \frac{1}{2} \rho w^3$, where w is the daily mean wind speed and ρ is the air density, which is assumed to be constant at 1.23 kg/m^3 for the North American ACI case and is 1.3 kg/m^3 at sea level, the values of the daily wind speed data are converted to wind power (WP). Wind power is chosen because it has been demonstrated that the effects of strong winds, i.e. damages, are proportional to WP rather than to w . The 90th percentile of wind power ($WP90$), across the monthly reference period is determined using the same procedure mentioned above. The following equation represents the standardized anomaly of the wind power.

$$W_{std} = \frac{WP90 - \mu_{ref}(WP90)}{\sigma_{ref}(WP90)} \quad (7)$$

Lastly, it is considered that the sea level (S) component should also be included in the ACI for coastal regions. Tide gauges monitor sea level relative to the land below, but as the land is shifting, they might not accurately reflect the current sea level. The ACI sea level component evaluates the combined influence of the generally rising seas and the rising/dropping land on coastal shorelines. The standardized anomaly of the sea level is given as follows.

$$S_{std} = \frac{S - \mu_{ref}(S)}{\sigma_{ref}(S)} \quad (8)$$

The percentage of coastal grid points relative to all grid points in a region is known as f_S in the gridded representation of the UK-European ACI (Curry, 2015). Due to the fact that the variable f_S , $0 < f_S \leq 1$ only affects a small portion of the continent's or a specific region's total area, it is included as an adjustment to the sea level contribution to the ACI which is shown in Equation (9).

3.2. The ACI as a Compound Indicator

The complexity of data-based studies prompts researchers to combine many indicators into a single index (Bruggemann and Patil, 2010). Although weighted sums are frequently used to aggregate data, there are certain drawbacks and difficulties of selecting appropriate weights in order to calculate the compound indicator. First of all, the aggregation could lead to the loss of indicator information, i.e. the information collected in a single compound indicator gets interlaced. When multiple indicators have the same characteristics, it may be undesirable for decision-makers to give them more weight than needed.

As a result, compound indicators' ability to offer an efficient metric system of measurement is particularly beneficial (Bruggemann and Patil, 2011). The ACI, a compound index as a function of the components introduced in Section 3.1, is defined as follows.

$$ACI = \text{mean}(T90_{\text{std}} - T10_{\text{std}} + P_{\text{std}} + D_{\text{std}} + W_{\text{std}} + f_S S_{\text{std}}) \quad (9)$$

There, the usage of standardized anomalies offers a useful method of integrating these indicators in an easy-to-understand and relevant way. The method maintains the accuracy of the component values while allowing the combination of such fundamentally dissimilar numbers in a single index. The standardized anomaly for any given indicator represents how abnormal that month's or season's value is in comparison to that period's mean and standard deviation. As a result, each component uses the same notation of subscript "std", and is expressed in units of the standard deviation of that parameter. This adheres to the approach suggested by Hansen et al. (1998).

4. Application

In this study, the ACI, which is utilized in North America and Australia and being built in Europe and India, has been calculated for Ankara, the capital city, as a pilot application for Turkey. The components of the ACI defined in Section 3.1 are taken from the NASA POWER gridded data set which is available online (<https://power.larc.nasa.gov/>). We searched data for climatic variables used in the ACI, which are high and low temperature, precipitation, consecutive dry days, wind and sea level, and we used data from 1981 to 2021 in our analyses.

The ACI does not include a sea level component since Ankara lacks an oceanic shoreline, which means we take $f_S = 0$ in Equation (9). The mean of the other components is used to determine the ACI for Ankara as in Midwest (MID) region for North America ACI case, i.e.

$$ACI = \frac{1}{5}(T90_{\text{std}} - T10_{\text{std}} + P_{\text{std}} + W_{\text{std}} + D_{\text{std}}) \quad (10)$$

Equation (10) is used in order to calculate the ACI for Ankara as an application in our study.

4.1. The Calculation of the ACI

In order to calculate standardized anomalies of the variables, a reference period must be determined first. We decide to use the years 1981 to 2010 as our reference period due to the lack of information, and because of the fact that it is more recent and that Australian ACI and UK-European ACI also use this range. All calculations are made using R programming in this study.

4.1.1. Threshold Determination for Extreme Weather Variables

In order to determine the frequency of extreme weather events, threshold values were computed for the variables in Equation (10). Once the threshold values are determined, it indicates the frequency of extreme weather by the number of days that fall below the 10th threshold value and exceed 90th threshold value of the relevant climate variable.

If we examine each climate variable in Equation (10) individually, the frequency of the extremes (the number of days exceeding 90% threshold values) for the variable $T90_{\text{std}}$ are indicated as $TX90$ and $TN90$ given in Equation (1) whereas the frequency of the extremes (the number of days falling behind 10% threshold values) for the variable $T10_{\text{std}}$ are indicated as $TX10$ and $TN10$ given in Equation (2). Similarly, the frequency of the extremes (the number of days exceeding 90% threshold values) for the variable W_{std} is indicated as $WP90$ given in Equation (7). Apart from these variables, for P_{std} and D_{std} , we calculate $Rx5\text{day}$ using Equation (3) and CDD using Equation (4) instead of threshold determination.

Zhang et al. (2005) propose to use 5CD technique which was utilized to determine the threshold required to identify extreme weather events. According to this method, data from five consecutive days centered on the day of interest are used to estimate thresholds. When a typical 30-year base period is adopted, the daily thresholds are, in fact, percentiles computed from samples of no more than $5 \times 30 = 150$ days of data.

As an illustration, for determining the threshold value to be used to determine whether an extreme weather situation occurs for a variable on January 12, the values on January 10, 11, 12, 13, and 14 are taken for each year over the complete reference period of 30 years. When the values of these 150 days are ordered as $y_1 < y_2 < \dots < y_{15} < \dots < y_{135} < \dots < y_{150}$ where y_i denotes the value of the i^{th} order statistics, the value of the 15th day ($150 \times 0.10 = 15$)

is the 10% threshold value whereas the value of the 135th day ($150 \times 0.90 = 135$) is taken as the 90% threshold value.

4.2. The Analysis of the ACI and Its Components

Extreme weather variables, which are single components of the ACI, and the ACI generated by combining them will be addressed in this section. Before calculating the ACI, we firstly present the descriptive statistics of the raw data of the climatic variables included in the ACI, which are wind speed, wind power, high temperatures, low temperatures, and total precipitation, respectively.

Table 3. Descriptive statistics of raw weather variables

Descriptive Statistics	w (m/s)	WP (W)	T90 (°C)	T10 (°C)	P (mm)
<i>n</i>	14,976	14,976	14,976	14,976	14,976
<i>Minimum</i>	0.6	0.13284	-10.32	-23.43	0
<i>Maximum</i>	11.23	870.9923	39.83	22.07	49.88
<i>1.Quartile</i>	2.32	7.679608	7.79	-2.03	0
<i>3.Quartile</i>	3.94	37.61524	25.39	10.6	0.67
<i>Mean</i>	3.247715	32.8642	16.53928	4.018337	1.115182
<i>Median</i>	3.03	17.10815	16.77	4.1	0.03
<i>Stdev</i>	1.306309	51.38992	10.2714	7.6323	2.800158
<i>CV</i>	0.402224	1.563705	0.621031	1.899368	2.510943
<i>Skewness</i>	1.147054	5.548769	-0.07774	-0.18279	4.679596
<i>Kurtosis</i>	2.273153	49.59994	-1.06211	-0.74701	33.55473

The temperature anomalies, which are calculated as a combined indicator of high and low temperatures, are two important components of the index. These factors stand apart from the others since they have an integrated effect on the index. For this reason, the graph below shows a composite temperature indicator. The five-year moving average of $T90_{std}$ and $T10_{std}$, which are standardized anomalies for high and low temperatures, and the composite indicator of these two ($T90_{std} - T10_{std}$) are given in the chart below.

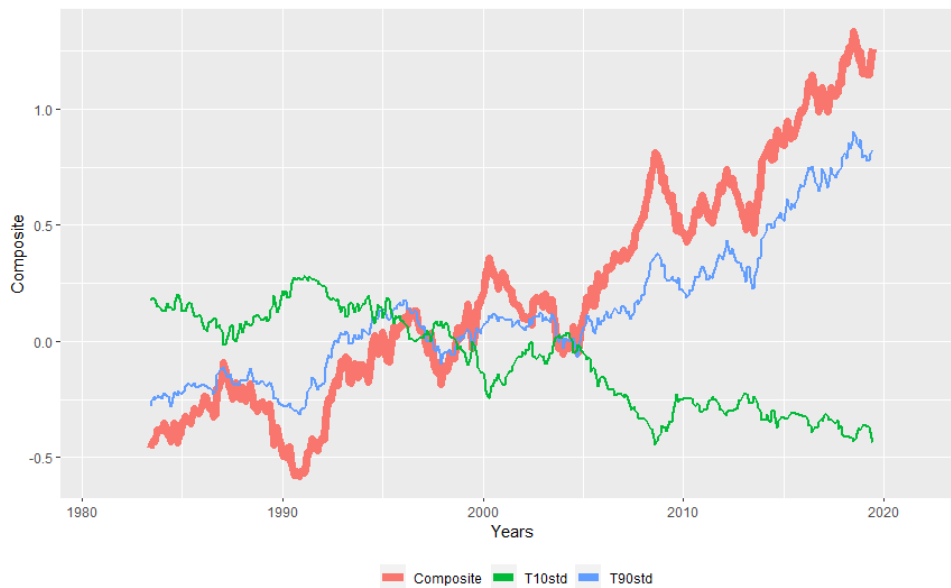


Figure 1. The five-year moving average of standardized anomalies of high and low temperatures and their composite indicator

As seen in Figure 1, Ankara has experienced increasingly extreme temperatures since the start of the reference period. The fact that standardized minimum temperatures, $T10_{std}$, have been declining under zero since the end of the 1990s indicates that extreme minimum temperature observations have become less frequent than they were during the reference period, while extreme maximum temperature observations have become more frequent than they were during the reference period.

Having calculated the standardized anomalies of the each component in Equation (10), the ACI for Ankara is calculated. The five-year moving average of the ACI is represented as follows.

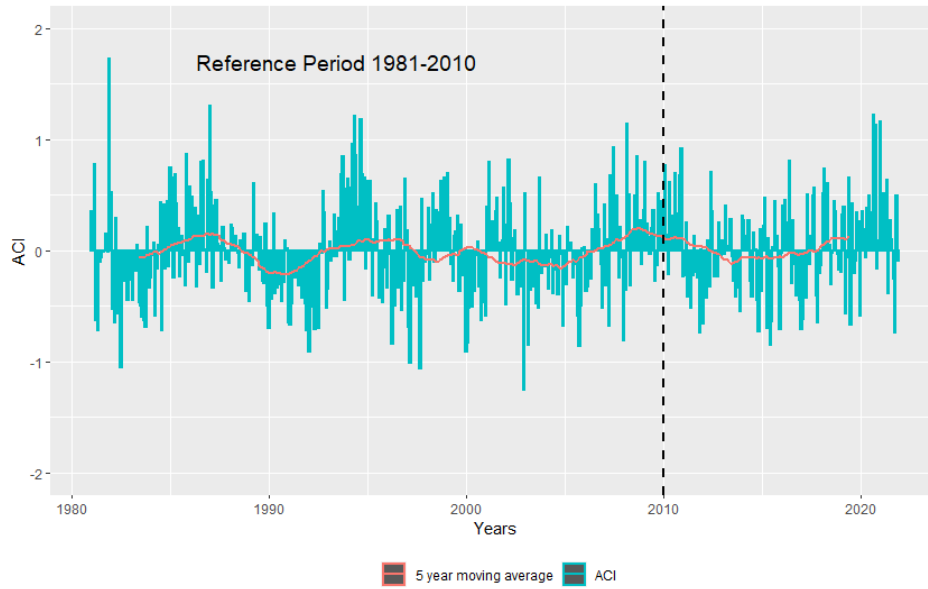


Figure 2. The ACI (the five-year moving average and monthly) for Ankara

Figure 2 shows that the ACI averages zero for the 1981-2010 reference period. The graph demonstrates that the average ACI remains close to zero, indicating that an increase in the frequency of climate extremes is not expected for Ankara in the future.

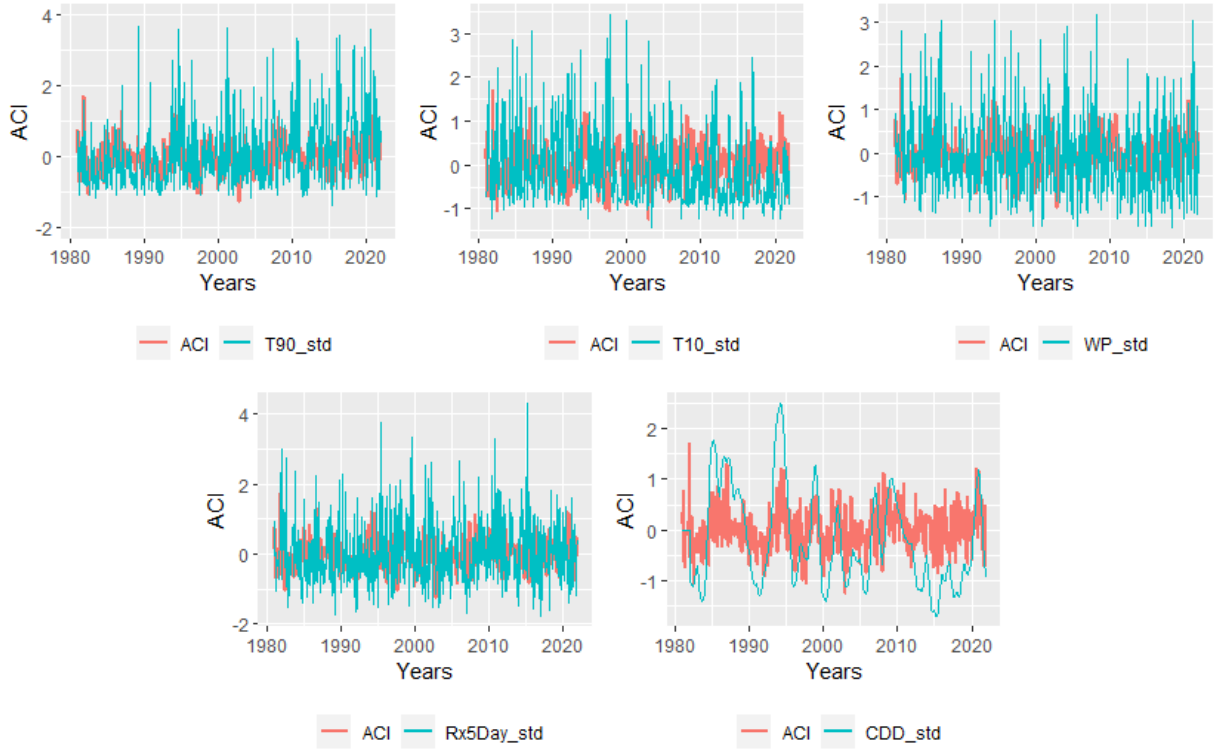


Figure 3. The ACI (monthly) and its components (monthly) for Ankara

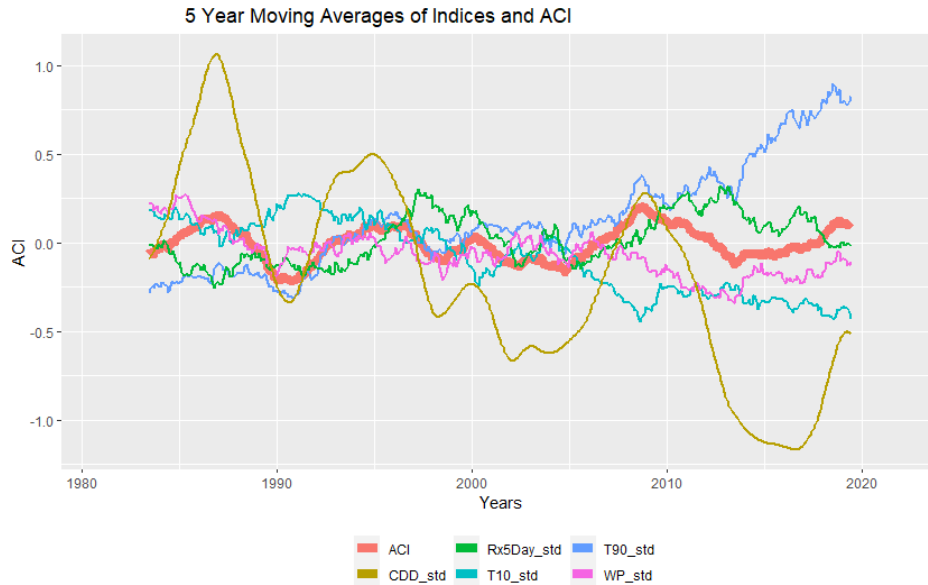


Figure 4. The five-year moving average of the ACI and its components for Ankara

According to Figures 3 and 4, it is seen that all components except $T10_{std}$ move in the same direction as ACI. The symmetry of $T10_{std}$ over the x -axis also moves in the same direction as ACI since $T10_{std}$ joins to ACI formula with a negative sign. In this context, it may be concluded that no component has a greater impact on the ACI than the others by examining the ways in which the indicators affect the ACI collectively. This outcome is not unexpected given that the index is determined by taking the arithmetic mean of its components rather than the weighted mean.

In addition to the graphical representation, the descriptive statistics of the monthly ACI are also illustrated in the following table.

Table 4. Descriptive statistics of monthly ACI for Ankara

<i>Descriptive Statistics</i>	<i>January</i>	<i>February</i>	<i>March</i>	<i>April</i>	<i>May</i>	<i>June</i>	<i>July</i>	<i>August</i>	<i>September</i>	<i>October</i>	<i>November</i>	<i>December</i>
<i>Minimum</i>	-0.9117	-0.9075	-1.0136	-0.8369	-0.7231	-0.8472	-1.0530	-0.7209	-1.0649	-0.8566	-0.7440	-1.2551
<i>Maximum</i>	1.2991	0.7972	1.1359	0.9545	1.2091	0.8549	0.9233	0.7914	1.2224	1.1305	0.8636	1.7190
<i>1.Quartile</i>	-0.4606	-0.3194	-0.2630	-0.3566	-0.2703	-0.2755	-0.2919	-0.2743	-0.3267	-0.3291	-0.2746	-0.3246
<i>3.Quartile</i>	0.4147	0.3788	0.4058	0.2495	0.3196	0.1999	0.2609	0.2677	0.3887	0.2274	0.2445	0.1894
<i>Mean</i>	-0.0311	0.0316	0.0795	-0.0309	0.0413	0.0197	-0.0371	0.0265	0.0356	-0.0310	-0.0463	-0.0326
<i>Median</i>	-0.1386	0.0942	0.1285	-0.0569	0.0378	0.0464	-0.0420	0.0602	-0.0158	-0.1595	-0.1271	-0.0974
<i>Stdev</i>	0.5541	0.4519	0.4780	0.4157	0.4173	0.3987	0.3812	0.3537	0.4949	0.4605	0.3845	0.5179
<i>CV</i>	-17.8392	14.3049	6.0162	-13.4437	10.0993	20.2010	-10.2877	13.3490	13.8905	-14.8501	-8.3015	-15.8834
<i>Skewness</i>	0.3813	-0.2768	-0.0762	0.0949	0.3764	0.2013	-0.2567	0.0660	0.4467	0.4553	0.2912	0.7727
<i>Kurtosis</i>	-0.6596	-0.9427	-0.4860	-0.6298	-0.1414	-0.5294	0.1861	-0.6276	-0.1173	-0.4951	-0.5445	1.8387

4.2.1. Time Series Analysis of the ACI

Beside the graphical and statistical analysis of the ACI, time series modeling is considered helpful for future forecasting. Using the values of the ACI from January 1981 to December 2021, we find that the series is stationary based on the Augmented Dickey-Fuller test since $p = 0.01 < 0.05$ where alternative hypothesis represents stationarity. In this situation, it is possible to analyze the series without any differencing.

Table 5. Fit results of time series models

Models	BIC	AIC	Log-Likelihood
ARIMA(0, 0, 1)	577.37	564.77	-279.39
ARIMA(1, 0, 0)	568.31	555.72	-274.86
ARIMA(1, 0, 1)	547.23	530.44	-261.22
ARIMA(2, 0, 1)	552.81	531.82	-260.91
ARIMA(1, 0, 2)	552.67	531.67	-260.84
ARIMA(3, 0, 1)	556.10	530.91	-259.46
ARIMA(1, 1, 1)	564.49	547.71	-269.49
ARIMA(2, 0, 1)(1, 0, 0)₁₂	552.79	531.79	-260.90

When we examine the models that can be applied for the ACI series, the ARIMA(1,0,1) model is the best model according to the BIC and AIC information criteria, and ARIMA(2,0,1)(1,0,0)₁₂ could be the most suitable model according to the log-likelihood. In addition to these, it is necessary to check whether the errors are white noise processes. The following table represents the results of Ljung-Box Test.

Table 6. Ljung-Box test results

Models	<i>X-squared</i>	<i>p-value</i>
ARIMA(1, 0, 1)	0.32798	0.5669
ARIMA(2, 0, 1)(1, 0, 0)₁₂	0.00444	0.9468

According to the results in Table 5 and Table 6, the most suitable model for the series is the ARIMA(1,0,1) model.

5. Conclusion and Further Study

Insurance companies need to be able to adequately price, pool, and spread risk in order to remain sustainable. However, as climate parameters change, modeled losses become more unpredictable. This makes it more difficult for insurers to recognize their tail risk, or the possibility that significant catastrophic losses could endanger solvency. To determine whether there is an increasing occurrence and risk of weather extremes, insurers must consider the frequency of severe weather. However, the majority of climatic data is presented as averages throughout time, which insurance actuaries do not find useful. The ACI studies appear to be effective to measure the anomalies that could be seen as the indicators of climate-related actuarial risks.

According to the existing studies and the results of this paper, it must be noted that the primary problem of obtaining ACI is choosing the best gridded dataset for the weather extremes rather than altering how the index is formulated. Therefore, our aim for further studies is to extend our application from Ankara to Turkey.

The potential uses of the ACI could be summarized as insurance applications (developing and pricing new insurance products and improving the measurement of tail risk), practices of businesses and financial institutions (developing and pricing new climate-related financial instruments and improving own risk management skills), and government administration (improving preparation and budgeting for disasters and “Climate Action” as a SDG) (Kotnala et al., 2018). Therefore, the ACI can be altered by including components specific to the area of interest for future computations that are more detailed, such as the hail component for car insurance. This suggestion could be handled in the context of Actuaries Climate Risk Index (ACRI).

More specifically, it is thought that in further research, a classification on a regional basis would be made in order to extend this application for Ankara to the entire country. In terms of sales and marketing, it is anticipated that using Turkey’s existing seven geographical regions will be more practical; nonetheless, the Köppen climate classification (see Lohmann et al., 1993 for detail) appears to be one of the most useful techniques for reflecting geographical information.

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A Comparison on Performances of Differential Evolution Algorithm and Genetic Algorithm in Determining the Biasing Parameter k of Ridge Regression

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Abstract

Ridge Regression is a very common way of the remedies for dealing with the “multicollinearity problem” in multiple regression analysis. Although it can provide much more consistent estimates than the ordinary least squares does, there is still a problematic issue in the use of Ridge Regression, which is the choice of biasing parameter k . In this study we propose the use of some Artificial Intelligence Algorithms, such as genetic and differential evolution, for choosing the optimal k value by not allowing to increase too much the mean absolute prediction error while reducing the variation inflation factors and condition number.

Keywords: Ridge Regression; Genetic Algorithm, Differential Evolution Algorithm, MAPE, Variance Inflation Factor, Condition Number

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Ridge Regresyonda Yanlılık Parametresi k 'nın Belirlenmesinde Genetik ve Diferansiyel Gelişim Algoritmalarının Performanslarına Dair Bir Karşılaştırması

Özet

Çoklu regresyonda karşılaşılan “çoklubağlantı” problem için en yaygın olarak önerilen yaklaşım Ridge Regresyondur. Ridge regresyon en küçük kareler yönteminden daha tutarlı tahminler sağlamasına rağmen yanlılık parametresi k 'nın belirlenmesi hala çözülmesi gereken bir meseledir. Bu çalışmada optimal k değerini bulmak için Yapay Zeka Tekniklerinden olan Genetik Algoritma ve Diferansiyel Gelişim Algoritması'nın kullanımı önerilmiştir. Bu yaklaşımların uygulanmasında varyans büyütme faktörü ile şartlı sayı gibi çoklubağlantı probleminin teşhisinde kullanılan göstergeler küçültülmeye çalışılırken ortalama mutlak yüzdelik hatanın çok büyümemesini kontrol altında tutarak algoritmalar geliştirilmiştir.

Anahtar kelimeler: Ridge Regresyon; Genetik Algoritma, Diferansiyel Gelişim Algoritması, Ortalama Mutlak Yüzdelik Hata, Varyans Büyütme Faktörü, Şartlı Sayı

1. Introduction

Multiple Regression analysis is a most powerful statistical tool for evaluating the relationship between the dependent variable and the explanatory variables. If it is believed that true relationship between the dependent variable and the independent variables is linear then the model

$$Y_i = \beta_0 + \beta_1 X_{1i} + \dots + \beta_p X_{pi} + \varepsilon_i$$

, which is called a multiple regression model, can be used. This model makes some assumptions on the random error term. These assumptions are that errors have zero mean, $E(\varepsilon_i) = 0$, and constant variance $Var(\varepsilon_i) = \sigma^2$, and are mutually uncorrelated $Cov(\varepsilon_i, \varepsilon_j) = 0$ for $i \neq j$. One another important assumption of the multiple regression model is that there are no any severe or exact linear independencies among the explanatory variables. When you study the real life problems with too many explanatory variables, the linear dependencies among the independent variables can be inevitable. In that case ridge regression can provide biased but much more consistent estimates. This technique is firstly introduced by Hoerl and Kennard (1970 a,b). They provided to decrease the variances of the parameters estimates by adding a positive small number to the diagonal element of the design matrix. Since then many researchers worked on it. As mentioning very briefly these are Hoerl A.E., Kennard R.W., Baldwin K.F. (1975), Hoerl A.E., Kennard R.W. (1976), Vinod H.D. (1976), Gibbons D.G. (1981). There are some other papers which contributes on the choice of k value. For example; Mardikyan S., Çetin E. (2008), Praga-Alejo et al (2008), Ahn, J.J, et al (2012), Khalaf G. And Shukur G.(2005), Kibria B.M.G. (2003), Muniz G. Et all (2012). Uslu V. R et al (2014).

2. Multicollinearity

Multicollinearity is one of the serious problems in multiple regression analysis and depicts a condition in which two or more explanatory variables in the multiple regression model are highly linearly related with one another. Since the case happens, the struggling with this problem is very important. In multiple regression analysis the multicollinearity problem is defined as follows;

Let X_1, X_2, \dots, X_p be explanatory variables and a_1, a_2, \dots, a_p scalars which at least one of a_j is not zero. If the relationship

$$a_1 X_1 + a_2 X_2 + \dots + a_p X_p \cong 0$$

exists, where \cong denotes approximate equality, then the situation is referred as the multicollinearity problem. Multicollinearity implies that $X'X$ is near singular and at least one eigenvalue is very close to zero. In this case $X'X$ can be invertible then the parameter estimates can be found but their standard errors are very large than it should be. High variances of the regression coefficients may drastically reduce the precision of estimates. As a

result of this some variables may be excluded from the model because they are not significant in the sample even though they are important in the population. Therefore, the detecting of this problem is very important.

There are some diagnostics to detect it: These are;

- a. **Variance Inflation Factors (VIF_j):** This measure calculated for each explanatory variables is actually the corresponding diagonal element of the inverse of the correlation matrix ($X'X$) of explanatory variables.

$$VIF_j = 1/(1 - R_j^2)$$

where R_j^2 is the determination coefficient of the j th explanatory variable regressing on the remaining variables. The general rule of thumb there is a serious multicollinearity problem on the data set if one or some VIF values are greater than 10. (Wooldridge, J. M, 2000)

- b. **The eigenvalues of the correlation matrix($X'X$) :** Let $\lambda_1, \lambda_2, \dots, \lambda_p$ be the eigenvalues of the correlation matrix. If there is one or more severe collinearity between the columns of matrix X, this causes some of the eigenvalues to be very close zero. In a very ideal case, which is the orthogonality between columns of X, the sum of invers of eigenvalues is equal to the number of the explanatory variables

$$\sum_{i=1}^p \frac{1}{\lambda_i} = p$$

As the sum is going apart from p then the severity of multicollinearity is increasing (Belsley, Kuh and Welsch, 1980).

- c. **Condition Number:** It is defined as the ratio of the maximum eigenvalue to the minimum eigenvalue. If it lies between 30 and 100 it signs a moderate multicollinearity and is greater than 100 the data has a severe multicollinearity problem

$$Condition\ Number(CN) = \frac{\lambda_{max}}{\lambda_{min}} < 30$$

- d. where λ_{max} and λ_{min} is the maximum and minimum eigenvalues of the correlation matrix, respectively (Belsley et al, 1980).

3. Ridge Regression

The multiple regression model is given by

$$Y = X\beta + \varepsilon \tag{1}$$

In presence of multicollinearity there are several remedies that we can apply, for avoiding from *its* undesirable effects on the estimates. Ridge regression is one of the remedies mostly employed. It was firstly proposed by Hoerl and Kennard (1970 a, b). In this method the estimates of the regression coefficients are obtained with a little bias guaranteed a smaller variance by adding a very small positive number in the diagonal elements of $X'X$. While the least squares estimators of regression coefficients are

$$\hat{\beta} = (X'X)^{-1}X'Y \tag{2}$$

the ridge estimators are introduced as

$$\hat{\beta}_R = (X'X + kI)X'Y \tag{3}$$

where k is a very small constant determined by the researcher. Here ($X'X$) is in the correlation form. Gauss Markov Theorem states that under the standard assumptions about errors; such as errors have expectation zero, are uncorrelated and have the equal variances; the least squares estimators of the parameters of the model in (1) are linear, unbiased and have the minimum variances. But there is no guarantee that the variance of $\hat{\beta}$ will be small. For this purpose the ridge estimator estimates β with a bias but a smaller variance than the least squares estimators' one. The mean squared error of $\hat{\beta}_R$ we can easily see that

$$MSE(\hat{\beta}_R) = E(\hat{\beta}_R - \beta)^2 = Var(\hat{\beta}_R) + [E(\hat{\beta}_R) - \beta]^2 \tag{4}$$

can be made small than the mean squared error of $\widehat{\beta}$ which is equal to variance of $\widehat{\beta}$ since there is no bias in it.

The ridge estimator is actually the linear transformation of the least squares estimator.

$$\begin{aligned}\widehat{\beta}_R &= (\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}\mathbf{X}'\mathbf{Y} \\ &= (\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}(\mathbf{X}'\mathbf{X})\widehat{\beta} = \mathbf{Z}\widehat{\beta}\end{aligned}\quad (5)$$

The expected value of ridge estimator tells us that it is also an biased estimator of β .

$$E(\widehat{\beta}_R) = E(\mathbf{Z}\widehat{\beta}) = \mathbf{Z}\beta \quad (6)$$

The variance-covariance matrix of $\widehat{\beta}_R$ is

$$\begin{aligned}\text{Var}(\widehat{\beta}_R) &= \text{Var}(\mathbf{Z}\widehat{\beta}) = \mathbf{Z}\text{Var}(\widehat{\beta})\mathbf{Z}' \\ &= \mathbf{Z}(\sigma^2(\mathbf{X}'\mathbf{X})^{-1})\mathbf{Z}' \\ &= \sigma^2(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}(\mathbf{X}'\mathbf{X})(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}\end{aligned}\quad (7)$$

Furthermore, VIF values based on the ridge estimators are defined as the diagonal elements of the matrix

$$(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}(\mathbf{X}'\mathbf{X})(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}$$

On the other side since the least squares estimator is unbiased, the mean squared error will be the variance of the estimator.

$$\begin{aligned}MSE(\widehat{\beta}) &= E(\widehat{\beta} - \beta)'(\widehat{\beta} - \beta) = \text{Tr Var}(\widehat{\beta}) \\ &= \sigma^2 \text{Tr}(\mathbf{X}'\mathbf{X})^{-1} = \sigma^2 \sum_{j=1}^p \frac{1}{\lambda_j}\end{aligned}\quad (8)$$

where λ_j is the j^{th} eigenvalues of $\mathbf{X}'\mathbf{X}$. Contrarily the mean squared error of ridge estimator is decomposed into two parts as below.

$$\begin{aligned}MSE(\widehat{\beta}_R) &= \text{Tr Var}(\widehat{\beta}_R) + \text{Bias}^2 \\ &= \sigma^2 \text{Tr}[(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}(\mathbf{X}'\mathbf{X})(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-1}] + k^2 \beta'(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-2}\beta \\ &= \sigma^2 \sum_{j=1}^p \frac{\lambda_j}{(\lambda_j + k)^2} + k^2 \beta'(\mathbf{X}'\mathbf{X} + k\mathbf{I})^{-2}\beta \\ &= \gamma_1(k) + \gamma_2(k)\end{aligned}\quad (9)$$

First part is the sum of variances of all the $\widehat{\beta}_R$. The second part is considered the square of a bias. It is obvious that the total variance decreases as k increases, while the squared bias increases. Therefore the possibility exists that there are admissible nonzero values of k for which

$$MSE(\widehat{\beta}_R) < MSE(\widehat{\beta})$$

If it can be done $\text{Var}(\widehat{\beta}) > \text{Var}(\widehat{\beta}_R)$ can be satisfied. In order to understand the relationship among the variance, bias and k , there will be more informative to have a look at the graph, which is well known by the researchers dealing with ridge regression, presented in Figure 1. All of the related proofs can be accessed from the paper by Hoerl and Kennard (1970a).

The residual sum of squares for the ridge estimator is

$$\begin{aligned}SSE(\widehat{\beta}_R) &= (\mathbf{Y} - \mathbf{X}\widehat{\beta}_R)'(\mathbf{Y} - \mathbf{X}\widehat{\beta}_R) \\ &= (\mathbf{Y} - \mathbf{X}\widehat{\beta})'(\mathbf{Y} - \mathbf{X}\widehat{\beta}) + (\widehat{\beta}_R - \widehat{\beta})'\mathbf{X}'\mathbf{X}(\widehat{\beta}_R - \widehat{\beta})\end{aligned}\quad (10)$$

First term in the right side of the equation (10) is the residual sum of squares for the least square estimator and the second term is actually the quadratic form of $(\widehat{\beta}_R - \widehat{\beta})$. This implies that as k increases the residual sum of squares of ridge estimator increases and consequently the determination coefficient R^2 based on Ridge decreases. Therefore, the ridge estimate will not necessarily give the best fit to the data when we are more interested in obtaining a stable set of parameter estimates.

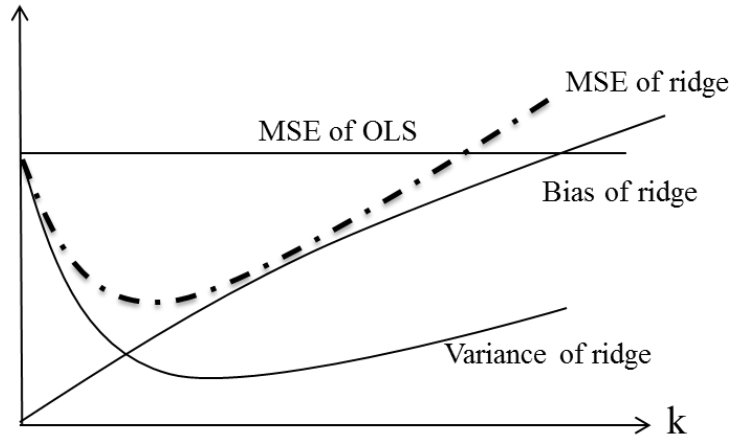


Figure 1: The relationships among variance,bias and k

As we can easily see that the choosing a value of k is a crucial issue in ridge regression. Ridge trace is one of the methods that we can apply. It is a plot of the elements of the ridge estimator versus k usually in the interval $(0, 1)$. From the ridge trace the researchers can see that at a reasonable k value the estimates become stable (Hoerl and Kennard, 1970b). Marquardt and Snee (1975) suggest using only 25 values of k , spaced approximately logarithmically over that interval.

The optimal k value can be found by examining the orthogonal form of the regression model. It is

$$Y = X^* \alpha + \varepsilon \quad (11)$$

where $X^* = XD$ and $\alpha = D'\beta$. The Generalized Ridge Estimators of α is

$$\widehat{\alpha}_R = (X^{*'}X^* + kI)^{-1}X^{*'}Y \quad (12)$$

The value of k_i which minimizes the MSE ($\widehat{\alpha}_R$) is

$$k_{iGR} = \frac{\sigma^2}{\alpha_i^2} \quad (13)$$

where σ^2 is the error variance and α_i is the i th element of α (Hoerl and Kennard, 1970a,b). When the actual values are not known the formula will be

$$k_{iGR} = \frac{\widehat{\sigma}^2}{\widehat{\alpha}_i^2} \quad (14)$$

where the estimates are obtained from the least squares. Alternative forms of the formula based on $\widehat{\alpha}$ for k can be respectively given as follows;

1. The harmonic mean of k_{iGR} ; $k_{HR} = \frac{p\widehat{\sigma}^2}{\sum \widehat{\alpha}_i^2}$ (Hoerl et al., 1975) (15)

2. The geometric mean of k_{iGR} ; $k_{GM} = \frac{\widehat{\sigma}^2}{\prod (\widehat{\alpha}_i^2)^{1/p}}$ (Kibria, 2003) (16)

3. The median of k_{iGR} ; $k_{MED} = Median(k_{iGR}) = Median\left(\frac{\widehat{\sigma}^2}{\widehat{\alpha}_i^2}\right)$ (Kibria,2003) (17)

Hoerl, Kennard and Baldwin (1975) suggested another method for finding k value which is given as

$$k = \frac{p\widehat{\sigma}^2}{\widehat{\beta}'\widehat{\beta}} \quad (18)$$

where $\widehat{\sigma}^2$ and $\widehat{\beta}$ are the least squares estimates and this approach is called “ordinary ridge regression” (ORR).

Hoerl and Kennard (1976) introduced an iterative method for finding optimal k value, which is called “iterative ridge regression” (IRG). In this method k is calculated as in below;

$$k_{IRG(t)} = \frac{p\hat{\sigma}^2(t-1)}{\hat{\beta}_{(t-1)}'\hat{\beta}_{(t-1)}} \quad (19)$$

where $\hat{\sigma}^2(t-1)$ and $\hat{\beta}_{(t-1)}$ are the corresponding residual mean square and the estimate vector of regression coefficients at $(t-1)$ th iteration, respectively. Generally, the initials are chosen the results from the least squares method.

Uslu (2014) proposes to find k value using the particle swarm optimization technique, regarding to the objective function defined as $\min\{MAPE(k) + \phi(k)\}$. In this objective function $\phi(k)$ is defined by the sum of VIF values providing that VIF's are limited to be less than 10. Praga Alejo et al. (2008) propose to find k by using the genetic algorithm with a problematic objective function and there is no limitation for VIF values. Therefore, the standard errors of the regression coefficients will be able to shrink too much and the bias will increase too much as well, which is the case we don't want.

4. The Proposed Approach for finding k

In this paper we redefine the objective function as in Equation (20) below and propose two approaches based on the genetic algorithm and differential evolution algorithm for finding the best value for k . The objective function is defined as

$$\min\{MAPE(k) + \phi(k) + \theta(k)\} \quad (20)$$

with subject to $0 < k < 1$; where $MAPE(k) = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad i = 1, 2, \dots, n$

$$\phi(k) = \begin{cases} 0, & \forall VIF_j < 10, & j = 1, 2, \dots, p \\ \sum_{j=1}^p VIF_j, & otherwise, & j = 1, 2, \dots, p \end{cases}$$

$$\theta(k) = \begin{cases} 0, & \forall CN_j < 30, & j = 1, 2, \dots, p \\ CN_j, & otherwise, & j = 1, 2, \dots, p \end{cases}$$

By defining this objective function in that way, we are trying to find k value which minimizes the mean absolute prediction error with subject to both VIF values and the condition number in order to be sure that there will be no more multicollinearity problem in the data set used.

In ridge regression as k increases the ill conditioning of $X'X$ is getting well. Therefore, the detectors of multicollinearity such as the condition number and VIF values are getting smaller but the residuals sum of squares increases.

Before we introduce both of the proposed algorithms, it would be good to remind how we generate genes and chromosomes. We have decided the number of genes as 4 because we know that k must be a very small positive number (Hoerl, 1962). Each gene is a number randomly generated from the interval (0, 9) because we want that each chromosome will be corresponded to a 4-digit number. Then this number is converted to the value between (0, 1) for k by using formula given in Equation 22.

Here are the steps of both proposed methods respectively.

The steps of the proposed method based on the differential evolution algorithm.

Step 1: Generate the initial population.

After NP (the size of the population or the # of chromosomes); D (the # of the genes in each chromosomes) are defined the initial population are generated by the equation (21).

$$x_{ji} = x_j^l + \text{round}(\text{rand}_j[0 \ 1] * (x^u - x^l)) \quad i = 1, 2, \dots, NP, \quad j = 1, 2, \dots, D \quad (21)$$

where

x_{ji} : j^{th} gene of i^{th} chromosome,

x^l, x^u : the lower and upper limits for a gen.

The number of genes D , the lower limit x^l and the upper limit x^u are to be chosen 4, 0 and 9, respectively. The aim of choosing $D=4$ is to determine the precision of the decimal part.

NP has to be at least 4 for the operators of the differential evolution algorithm to be implemented.

Step 2: Evaluate the values for k from the genes.

Each k value corresponding to the chromosomes are obtained from the following equation.

$$k_i = \frac{1}{10^D} \sum_{j=1}^D x_{ji} 10^{D-j} \quad i = 1, 2, \dots, NP, \quad j = 1, 2, \dots, D \quad (22)$$

Step 3: Apply the mutation operation.

3 chromosomes are randomly selected apart from the chromosome, which is called *the current chromosome*, symbolized by x , and is actually to be subjected to mutation operation. It is taken the difference between the first two of the 3 randomly selected chromosomes, and then it is multiplied by the scaling factor (F). And finally, it is added to the third chromosome and the final chromosome, which is called *the total chromosome*, is being generated.

With x_{r1}, x_{r2}, x_{r3} randomly chosen chromosomes, and F from the interval (0, 2),

$$n_{ji} = x_{j,r3} + \text{round} \left(\text{abs} \left(F * (x_{j,r1} - x_{j,r2}) \right) \right) \quad (23)$$

the total chromosome n is obtained. F is a real and constant factor $\in [0, 2]$ which controls the amplification of the differential variation $(x_{j,r1} - x_{j,r2})$ (Storn and Price, 1997). To be able to get the appropriate values for the genes we apply the following adjustment. Then the final total chromosome n_{ji}^* is replaced to the total chromosome as follows.

$$n_{ji}^* = \begin{cases} n_{ji} & x^l \leq n_{ji} \leq x^u \\ n_{ji} = 9, & n_{ji} > x^u \end{cases} \quad (24)$$

$$n_{ji} = n_{ji}^*$$

Step 4: Apply the crossover operation

The nominee chromosome for the new population is generated by using the current chromosome and the total chromosome (n). To do that, first of all random numbers are generated from the interval (0,1) for each genes. Then each random number are compared with the crossover ratio, which should be determined in the first step. With the following rule

$$u_{ji} = \begin{cases} n_{ji}, & \text{rand}(0,1) \leq co \vee j = j_{rand} \\ x_{ji}, & \text{otherwise} \end{cases} \quad (25)$$

The nominee chromosome (u) has been generated. With $j = j_{rand}$ at least one gene from the total chromosome has been transferred to the nominee chromosome.

Step 5: Calculate the fitness value and the selection

Fitness value is the value of $MAPE(k) + \phi(k) + \theta(k)$. After the mutation and cross over operation the fitness value of the nominee chromosome is calculated. If it is less than the one of the current chromosome the nominee chromosome, instead of the current chromosome, is replaced into the new population, otherwise the current chromosome remains in the next generation.

If we symbolize x_{G+1} , as the chromosome to be involved in the new population, the rule will be the as follows.

$$x_{i,G+1} = \begin{cases} u_i, & f(u_i) \geq f(x_i) \\ x_i, & \text{otherwise} \end{cases} \quad (26)$$

Step 6: The steps from 3 to 5 is repeated for all chromosome in the population, successively. The new generation has been constructed.

Step 7: The algorithm from Step 2 with the new generation constructed at Step 6 is repeated up to the iteration number (its). The best population will be reached at the end of the iteration. The chromosome with the best fitness value in this population will be the best solution of the problem.

The steps of the proposed method based on the genetic algorithm

Step1: Define the parameters of the genetic algorithm.

Let be ‘NP’ the number of chromosomes which means the size of population, ‘D’ the number of the gens in the chromosome, ‘co’ the ratio of crossover, ‘mr’ the ratio of mutation, ‘es’ the number of the chromosomes to be eliminated from the population and ‘itrs’ the number iteration.

Step2: Generate the initial population

$$x_{ji} = x_j^l + integer(rand_j[0\ 1] * (x^u - x^l)) \quad i = 1,2, \dots, NP, \quad j = 1,2, \dots, D \quad (27)$$

where the parameters are defined as in the step 1 of the previous algorithm.

Step 3: Evaluate the values for k from the genes

This step is the same as the step 2 of the previous algorithm. The fitness value based on the objective function is calculated by k values obtained from each chromosome of the initial population.

Step 4: Apply the Natural Selection.

Due to the principle of “the more strong the most possible to survive”, the ‘es’ chromosomes with the worst fitness value, are removed from the population. Then the ‘es’ chromosomes are regenerated as in the step 2.

Step 5: Apply the crossover operation.

In this step, the chromosomes are randomly paired with each other. The crossover ratio is compared with the randomly generated number from the interval (0, 1) for each pair. The crossover operation is applied to the pair with the random number, which is less than the ‘cr’. Then another random number from the integer interval (1, L-1) is also generated to decide which crossover point will be.

Step 6: Apply the mutation operation.

First of all, random numbers are generated from the interval (0, 1) for each chromosome to decide whether the mutation operation is applied, or not. These random numbers are compared to the mutation ratio. When the random number is less than the crossover ratio the crossover operation is applied to the corresponding chromosome. And again, another random number from the integer interval (1, L) is generated to decide which gene is regenerated in that chromosome.

Step 7: The Choice of k .

From Step 4 to Step 6 a new generation has been constructed. In order to reach optimal solution for k , these steps are repeated up to the iteration number. At the end of the iterations the final population has been constructed. The chromosome with the best fitness value will be the optimal solution.

5. Application

Our proposal approaches have been applied to the real data sets which are known as “Import Data” and “Longley Data”. We have chosen these data sets since we want to compare the results from our proposed methods with the results from the approaches in literature. The variables are imports (IMPORT-Y), domestic production (DOPROD-X1), stock formation (STOCK-X2) and domestic consumption (CONSUM-X3), all measured in billions of French francs for the years 1949 through 1959 (Chatterjee and Hadi, 2006). Longley’s data set is a classic example of the data with the problem multicollinearity (Longley, J.W., 1967).

Our proposal approaches were coded in MATLAB-2015. The programs based on DEA and GA are executed for the parameters as given below for both data sets.

The parameters for DEA;

- ❖ The number of iterations (*its*) as 50, 100, 150, 200.
- ❖ The number of chromosomes (NP) as 30, 40, 50, 60.

- ❖ The scaling factor (F) as 0.5, 0.8, 1.2.
- ❖ The crossover ration (cr) as 0.4, 0.5, 0.6, 0.7.

The parameters for GA;

- ❖ The number of iterations (its) as 50, 100, 150, 200.
- ❖ The number of chromosomes (NP) as 30, 40, 50, 60.
- ❖ The number of chromosomes to be eliminated (es) as 5, 8, 13, 17.
- ❖ The crossover ration (cr) as 0.65, 0.75, 0.80, 0.85, 0.95.
- ❖ The mutation ration (mr) as 0.005, 0.01, 0.05, 0.1.

For Longley Data the best result of MAPE was found as 0.210446 at $k = 0.1584$ from both DEA and GA. This result from DEA is obtained at $F = 0.5$, $cr = 0.6$, $NP = 30$ and $its = 50$ and from GA at $cr = 0.95$, $mr = 0.05$, $NP = 40$, $es = 8$ and $its = 50$. For Import Data the best result of MAPE is found as 0.126696 at $k = 0.0662$ from both DEA and GA. This result is obtained from DEA at $F = 0.5$, $cr = 0.6$, $NP = 30$ and $its = 50$ and from GA at $cr = 0.95$, $mr = 0.01$, $NP = 40$, $es = 8$ and $its = 100$. Table 1 and 2 provides the comparative results with the other techniques in the literature. Although the other techniques can provide the smaller k value but some VIF values and condition number seem still problematic. In our application k has been found as 0.1584 for Longley Data and as 0.0662 for Import Data from both DEA and GA. It has been observed that at these values of k obtained for both data sets all of VIF's are less than 10 and condition numbers are less than 30.

For the purpose of comparison of two proposed approaches we summarized the results obtained at different combinations of NP and its by fixing the other parameters such as F , cr , mr and es . Table 3 and 4 is represented to show these comparisons at $F = 0.5$, $cr = 0.6$ for DEA and at $cr = 0.85$, $mr = 0.05$ and $es = 8$ for GA for Longley Data. Table 5 and 6 is constructed to show the comparisons between DEA and GA for Import data at the same parameter's values. We have picked these parameters values among many trials that give the minimum MAPE, just as an example. From these tables we can conclude that DEA can reach the optimal value more often than GA. We should point out that at the different values for the parameters, which we have fixed at Table 3 and 4, we have reached the same conclusion. We can conclude that DEA has found the minimum MAPE value more often than GA.

Table 1: Longley Data. COEF: Coefficients, SE: Standard Errors of the coefficients.

	k	COEF	SE	VIF	CN	SSE	MAPE
Ordinary Least Squares	0	0.046	0.261	135.53	12220	0.00452	0.0887
		-1.014	0.948	1788.51			
		-0.538	0.130	33.62			
		-0.2047	0.0425	3.59			
		-0.101	0.448	399.15			
		2.48	0.617	758.98			
Harmonic Mean	0.0004	-0.0134	0.2202	87.3167	6242.9	0.0050	0.0753
		-0.2524	0.5122	472.1528			
		-0.4306	0.0780	10.9497			
		-0.1814	0.0400	2.8773			
		-0.2828	0.3164	180.2142			
		1.8797	0.4149	309.8213			
Geometric Mean	0.0021	0.0784	0.1931	46.6209	1824.7	0.0072	0.0938
		0.2467	0.1863	43.3779			
		-0.3449	0.0535	3.5720			
		-0.1511	0.0444	2.4598			
		-0.1801	0.2164	58.5586			
		1.1181	0.2485	77.1886			
Median From Kibria 2003	0.0019	0.0683	0.1949	48.8217	1984.7	0.0070	0.0915
		0.2320	0.1989	50.8888			
		-0.3485	0.0537	3.7031			
		-0.1526	0.0439	2.4802			

		-0.1962	0.2218	63.2613			
		1.1622	0.2577	85.3985			
Ordinary Ridge	0.00036	-0.0134	0.2203	87.3630	6249.9	0.0050	0.0753
		-0.2532	0.5127	473.0805			
		-0.4308	0.0781	10.9656			
		-0.1814	0.0400	2.8779			
		-0.2827	0.3166	180.3958			
		1.8805	0.4151	310.1863			
Iterative Ridge	0.0014	0.0379	0.1999	56.1977	2591.7	0.0064	0.0845
		0.1719	0.2456	84.8510			
		-0.3613	0.0552	4.2905			
		-0.1590	0.0426	2.5478			
		-0.2422	0.2392	80.4556			
		1.3094	0.2876	116.2878			
Eren 2014	0.0172	0.02	0.1168	9.99	262.88	0.0123	0.1378
		0.10	0.0459	1.54			
		-0.37	0.0590	2.55			
		-0.16	0.0516	1.95			
		-0.27	0.1000	7.32			
		1.44	0.0746	4.07			
Proposed Method with GA	0.1584	0.2472	0.0341	0.4040	29.9904	0.0259	0.2104
		0.2860	0.0230	0.1845			
		-0.1377	0.0557	1.0797			
		-0.0034	0.0515	0.9223			
		0.2341	0.0298	0.3084			
		0.2611	0.0193	0.1291			
Proposed Method with DEA	0.1584	0.2472	0.0341	0.4040	29.9904	0.0259	0.2104
		0.2860	0.0230	0.1845			
		-0.1377	0.0557	1.0797			
		-0.0034	0.0515	0.9223			
		0.2341	0.0298	0.3084			
		0.2611	0.0193	0.1291			

Table 2. Import Data. COEF: Coefficients, SE: Standard Errors of the coefficients.

	k		COEF	SE	VIF	CN	SSE	MAPE
Ordinary Least Squares	0		-0.3393	0.464	185.9975	742.9346	0.0081	0,1052
			0.2130	0.0343	1.0189			
			1.3027	0.464	186.1100			
Harmonic Mean	0.0016		-0.0297	0.2976	72.0916	462.4151	0.0086	0.1097
			0.2158	0.0351	1.0046			
			0.9922	0.2977	72.1348			
Geometric Mean	0.0035		0.1256	0.2153	34.8947	321.4231	0.0093	0.1235
			0.2169	0.0364	0.9972			
			0.8359	0.2154	34.9153			
Median From Kibria 2003	0.0021		0.0222	0.2704	58.1769	415.3280	0.0088	0.1206
			0.2162	0.0355	1.0022			
			0.9400	0.2705	58.2117			
Ordinary Ridge	0.0016		-0.0340	0.3001	73.3001	466.2798	0.0086	0.1097
			0.2157	0.0351	1.0048			
			0.9965	0.3002	73.3440			
Iterative Ridge	0.0042		0.1594	0,1969	28.5743	290.7252	0.0095	0.1137
			0.2171	0.0368	0.9952			
			0.8018	0.1970	28.5910			
Eren 2014	0.0090		0.2897	0.1212	9.99	171.7709	0.0103	0.1185
			0.2174	0.0380	0.98			
			0.6692	0.1213	10.0			

Proposed Method with GA	0.0662		0.4333	0.0305	0.5183	29.9801	0.0126	0.1267
			0.2080	0.0398	0.8803			
			0.4993	0.0305	0.5181			
Proposed Method with DEA	0.0662		0.4333	0.0305	0.5183	29.9801	0.0126	0.1267
			0.2080	0.0398	0.8803			
			0.4993	0.0305	0.5181			

Table 3: For DEA, MAPE/the iteration at which the optimal solution has been achieved for Longley Data.

Iteration \ NP	30	40	50	60
50	0,210446/21	0,210784/29	0,210446/34	0,210446/38
100	0,210446/14	0,210446/44	0,210446/51	0,210446/32
150	0,210446/29	0,210446/14	0,210446/14	0,210446/34
200	0,210446/25	0,210446/38	0,210446/62	0,210446/35

The optimal MAPE is obtained at F=0.5 and cr=0.6.

Table 4: For GA, MAPE/the iteration at which the optimal solution has been achieved for Longley Data.

Iteration \ NP	30	40	50	60
50	0,211497/16	0,211288/6	0,210657/3	0,210615/19
100	0,212245/3	0,210489/11	0,210784/27	0,210446/2
150	0,210489/18	0,210531/43	0,210446/44	0,210446/46
200	0,210657/153	0,210700/154	0,210489/79	0,210446/111

The optimal MAPE is obtained at cr=0.85, mr=0.05.

Table 5: For DEA, MAPE/the iteration at which the optimal solution has been achieved for IMPORT Data.

Iteration \ NP	30	40	50	60
50	0,126696/19	0,126715/42	0,126696/41	0,126696/28
100	0,126734/6	0,126696/32	0,126696/36	0,126696/46
150	0,126696/20	0,126696/21	0,126715/21	0,126696/31
200	0,126696/23	0,126715/16	0,126734/31	0,126696/31

The optimal MAPE is obtained at F=0.5 and cr=0.6.

Table 6: For GA, MAPE/the iteration at which the optimal solution has been achieved for IMPORT Data.

NP \ Iteration	30	40	50	60
50	0,126940/15	0,127089/20	0,126884/13	0,126977/11
100	0,126696/99	0,126734/80	0,126753/12	0,126828/4
150	0,126772/22	0,126696/62	0,126696/94	0,126734/133
200	0,126696/82	0,126696/85	0,126696/42	0,126696/47

The optimal MAPE is obtained at $cr=0.85$, $mr=0.05$.

6. Conclusion

As you can see from Table 1 and 2, at k found from both approaches, the standard errors of the regression coefficients have been decreased and MAPE, and consequently SSE, has not been allowed to increase too much. Also, we can say that the condition number as well as VIF values have been shrank to the desired level. Consequently, this result means that there is no more multicollinearity problem in the data sets.

Since we have taken into account condition number as well as VIF when MAPE was doing minimized, the proposed methods based on GA and DEA could have found the optimal solution for k and consequently minimum MAPE. Speaking of the performances of these two approaches we can say that there is not much difference between them. Both approaches find the same result, however the approach based on DEA finds this result more frequently than GA when we change the values of the parameters of the algorithms such as F , cr , mr and es . This result is true for both data sets.

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Bitkisel Ürün Verim Sigortası için Prim Oranlarının Belirlenmesi: Cihanbeyli, Çorlu ve Polatlı Örnekleri

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Özet

Günümüzde tarımsal faaliyetlerle uğraşan iş gücü piyasası ile üretim yapılabilecek tarım alanlarının azalması ve nüfusun artması gibi tarımsal üretimi etkileyen nedenlerin çoğalması, temel besin kaynaklarının üretiminin devam etmesi konusunu önemli bir hale getirmektedir. Bu bağlamda, tarımsal üretimi üstlenen çiftçilerin üretimine devam etmesi, üretimden kaynaklanan risklere karşı kendini güvende hissedebilmesi için önlemlerin alınması gerekmektedir. Dolayısıyla üretimi doğrudan etkileyen çevresel risklerin de etkisini azaltılabilecek sigorta poliçelerinin sunulması önem kazanmaktadır. Bu çalışmada, tarım sigortalarında kullanılan önemli bir sigorta uygulaması olan verim sigortası anlatılmış, Türkiye için buğday üretiminde buldukları illerde ilk sıralarda yer alan Cihanbeyli, Çorlu ve Polatlı ilçelerine ait 1991-2021 yılları arası buğday verim verileri kullanılarak verim sigortası için prim oranları elde edilmiştir. 31 yıllık buğday verisi, tarım sigortaları için sıkça kullanılan parametrik dağılımlardan; normal, beta ve parametrik olmayan gaussian kernel dağılımı yardımıyla incelenmiştir.

Anahtar Kelimeler: Verim Sigortası, Parametrik Dağılım, Gaussian Kernel

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Determination of Premium Rates for Crop Yield Insurance : Examples of Cihanbeyli, Çorlu and Polatlı

Abstract

The increase in factors that seriously affect access to food, such as the decrease in the labor market dealing with agricultural activities, the increase in the population and the decrease in the agricultural areas where production can be made, makes the issue of continuing the production of basic food sources important. In this purpose, it is needed to take precautions for the farmers, who assume the main role of agricultural production, to continue their production and to feel safe against the risks arising from production. Therefore, it is important to present insurance policies that can reduce the impact of environmental risks that directly affect production. In this study, crop yield insurance, which is an important insurance application used in agricultural insurance, is explained. Premium rates for yield insurance were obtained by using wheat yield data for the years 1991-2021 belonging to the provinces of Cihanbeyli, Çorlu and Polatlı, which are among the top cities in wheat production for Turkey. Normal, beta and non-parametric Gaussian kernel distributions were used for wheat yield data.

Keywords: Crop Yield Insurance, Parametric Distributions, Gaussian Kernel

1. Giriş

Artan nüfus ve tarım alanlarının azalması gibi geleceği tehdit eden gelişmeler, temel besin kaynaklarının üretiminin güvenli bir şekilde devam ettirilmesi konusunu da önemli bir hale getirmektedir. Çiftçinin tarımsal faaliyetlerinden dolayı herhangi bir gelir kaybı yaşamaması ve üretimine devam etmesi için sigorta sözleşmesi satın alması daha da önemli bir hale gelmektedir. Tarım sigortası ürünleri, çiftçiyi üretimden kaynaklanan hasarların finansal etkilerinden korumaktadır. Bu bağlamda kullanılan geleneksel tarım sigortaları, doğal afetler ve gelirin belli bir seviyenin altına düşmesi gibi çiftçinin gelirini olumsuz etkileyen risklere karşı bir koruma sağlamaktadır. Fakat bu sigorta ürünleri için tersine seçim (adverse selection) ve ahlaki-tehlike (moral hazard) gibi sigorta sözleşmelerini olumsuz etkileyen, daha çok teminat ödenmesine sebep olan riskler mevcuttur. Doğal olarak sigortalı kendi üretimi hakkında, sigorta şirketinden daha fazla bilgiye sahip olduğundan bu durumu kullanarak haksız kazanç elde etmekte ve bu durum sigorta şirketlerinin primleri yükseltmesine sebep olmaktadır. Sigortalılar için daha yüksek prim oranları çıktığından, primlere yapılan devlet desteğine rağmen, sigorta talebi düşmektedir. Bu sebepten dolayı, klasik tarım sigortaları dünya genelinde prime belirli oranda yapılan devlet katkılarıyla ayakta durmaktadır. Coble vd. (1997), Skees ve Reed (1986), Nelson ve Loehman (1987) çalışmalarında assimetrik bilginin piyasa başarısızlığına sebep olduğunu göstermişlerdir.

Verim sigortası, tarım sigortalarında kullanılan önemli bir sigorta uygulamasıdır. Sigorta şirketi tarafından önceden belirlenen, garanti edilmiş verim ve çiftçinin gerçekleşen verimi arasındaki fark kadar ödemenin yapılması mantığına dayanmaktadır. Verim sigortasına ilişkin prim oranlarını doğru bir şekilde elde edebilmek için öncelikle riskin istatistiksel dağılımının iyi belirlenmesi gerekmektedir. Botts ve Boles (1958), Just ve Weninger (1999) çalışmalarında tarımsal verim için parametrik bir dağılım olan normal dağılımı kullanmışlardır. Day (1965), Nelson ve Preckel (1989) ise çalışmalarında beta dağılımını kullanarak verim tahmini yapmışlardır.

Verinin kalın kuyruklu ya da iki tepeli (bimodal) olması gibi durumlarda, parametrik dağılımların kullanılması uygun olmamaktadır. Parametrik olmayan tahmin yöntemleri, sadece veriye bağlı olduğundan ve herhangi bir parametreye ihtiyaç duymadığından parametrik dağılımların yerine kullanılabilir yöntemlerdir (Xie, Xie, 2009). Goodwin ve Ker (1998), Ozaki vd. (2008), parametrik olmayan Gaussian Kernel tahmin edicisini kullanarak çeşitli tarım ürünlerine göre prim oranları hesaplamışlardır.

Bu çalışma için TÜİK'e ait (Türkiye İstatistik Kurumu) 1991-2021 yılları arası ilçe bazlı buğday verileri kullanılmıştır. Türkiye için yıllara göre bireysel çiftçi verilerinin olmamasından dolayı, ilçe bazlı veriler kullanılmıştır. Literatürde, bireysel verilerin yerine verim sigortası için il, ilçe ya da bölge bazlı verilerin kullanıldığı çalışmalar bulunmaktadır (Ozaki vd., 2008; Miranda, 1991; Skees vd., 1997).

Türkiye'de verim sigortası 2017 itibarıyla uygulamaya konulmuştur. Devlet Destekli İlçe Bazlı Kuraklık Verim Sigortası olarak yürürlüğe giren bu sigorta ürünü için tazminat; ilçenin gerçekleşen verim ortalaması ile ilçenin eşik verim değeri arasındaki fark baz alınarak hesaplanmaktadır. İlçenin gerçekleşen verim ortalaması için ilgili yıla ait hasat döneminde Tarım Sigortaları Havuzu (TARSİM) tarafından belirlenen referans parsellerde verim tespiti yapılacaktır.

Şahin vd. (2016) Türkiye'deki buğday bitkisel ürün sigortası için coğrafi tehlike bölgeleri bazında gerçekleşen hasar tutarlarını temsil eden istatistiksel dağılımı belirledikten sonra, aktüeryal adil prim hesaplamışlardır. Binici ve Zulauf (2006) Konya ili ilçelerine ait buğday verim verilerine üstel düzeltirme metodunu uygulayarak prim oranlarını elde etmişlerdir.

2. Materyal ve Yöntem

Bu çalışmada, TÜİK'e ait 1991-2021 yılları arası Cihanbeyli, Çorlu ve Polatlı ilçelerine ait ilçe bazlı buğday verileri kullanılmıştır. Öncelikle Cihanbeyli, Çorlu ve Polatlı ilçeleri için buğday verimi verisi, trend içerdiğinden, doğrusal trend modeli kullanılarak veri trendden arındırılmıştır. Daha sonra parametrik ve parametrik olmayan yöntemler verilere uygulanmış ve ilçelere ait buğday prim oranları elde edilmiştir. Çalışma için Excel ve R programları kullanılmıştır.

Sigorta işlemlerinde ödenecek teminatın ve primin doğru bir şekilde belirlenmesi için öncelikle ilgilenilen verinin modellemeye uygun olup olmadığı iyi araştırılmalıdır. Verinin trend, otoregresif etkiler ve değişen varyanslılık içermesi durumunda, veri bağımsız ve aynı dağılımlı olmayabilir. Bu sebepten dolayı, veriye istatistiksel modeller uygulanmadan önce, verinin düzeltilmesi gerekmektedir (Xie, Xie, 2009).

Verinin trend içermesi durumunda, veriyi trendden arındırmak için doğrusal ve doğrusal olmayan modellerin kullanıldığı çalışmalar literatürde önerilmiştir (Ye vd., 2015; Lu vd., 2017). Ozaki vd. (2008) veriyi trendden arındırmak doğrusal trend modelini kullanmışlardır. y , buğday verimini göstermek üzere doğrusal trend modeli,

$$y = \beta_0 + \beta_1 t + \varepsilon, \quad t = 1991, 1992, \dots, 2021 \quad (1)$$

biçimindedir. Burada β_0 , doğrusal modelin sabit terimini, β_1 , trend katsayısını ve ε ise model için hata terimini göstermektedir. Eşitlik 1'den tahmin edilen verim, verideki trendin büyüklüğünü (\hat{y}_{trend}) gösterdiğinden ε_t , modelin tahmin edilen hata değerini olmak üzere, yıllar için gözlenen verim aşağıdaki gibi gösterilir.

$$y_t = \hat{y}_t^{trend} + \varepsilon_t \quad (2)$$

Verideki trendin büyüklüğü belirlendikten sonra trendden arındırılmış verim (y_{trend}^0) aşağıda verilen eşitlik yardımıyla hesaplanmaktadır (14).

$$y_{trend}^0 = \frac{y_t}{\hat{y}_t^{trend}} \hat{Y}_T \quad (3)$$

Burada, \hat{Y}_T , Eşitlik 1'in tahmini sonucu elde edilen T . yıl tahmin değerini göstermektedir. Bu çalışmada $T = 2021$ olarak alınmıştır. 2021 yılının seçilmesinin sebebi, teknolojik gelişmelerin en yüksek temsil edildiği yıl olmasıdır. Eşitlik 3'ün kullanılmasının sebebi, veride değişen varyanslılık sorunu varsa bunu ortadan kaldırmasıdır.

Çalışmada, ilçe bazlı veriler için prim oranları, trend içeren ve trendden arındırılmış verim olmak üzere ayrı ayrı bulunmuştur. Gerçekleşen verimin, önceden belirlenen eşik değerden (hasar seviyesi) küçük olması durumunda ödenecek tazminat $S(c) = \max(c\bar{y} - y, 0)$ olmak üzere, Goodwin ve Ker (1998) prim oranını (π_r) bulmak amacıyla aşağıdaki eşitliği kullanmışlardır.

$$\pi_r = \frac{P(y < c\bar{y})(c\bar{y} - E(y/y < c\bar{y}))}{c\bar{y}} \quad (4)$$

Bu eşitlik için $P(y < c\bar{y})$ gerçekleşen verimin, önceden belirlenen eşik değer (hasar seviyesi) $c\bar{y}$ 'den küçük olması olasılığını; c , sigorta şirketi tarafından sağlanan teminat oranını ($0 < c < 1$) ve \bar{y} verim için beklenen değeri ($\bar{y} = \int_{-\infty}^{\infty} yf(y)dy$) göstermektedir. Gerçekleşen verimin, eşik değerden küçük olması koşulu altındaki beklenen değeri ise $E(y/y < c\bar{y})$ olarak ifade edilir. Eşitlik 4'ün pay kısmı, bu sigorta için sigortalı tarafından ödenecek primi göstermektedir. Primin eşik değere bölünmesiyle de prim oranı bulunmaktadır. $P(y < c\bar{y})$ ve $E(y/y < c\bar{y})$ için matematiksel gösterimler aşağıdaki gibidir.

$$P(y < c\bar{y}) = \int_0^{c\bar{y}} f(y)dy$$

$$E(y/y < c\bar{y}) = \frac{\int_0^{c\bar{y}} yf(y)dy}{\int_0^{c\bar{y}} f(y)dy}$$

Yukarıda verilen integrallerin çözümü için numerik çözümler kullanılmıştır. Verimin normal dağılıma sahip olduğu varsayılırsa, olasılık yoğunluk fonksiyonu,

$$f(y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

biçimindedir. Burada μ ortalamayı, σ standart sapmayı göstermektedir. Beta dağılımı için olasılık yoğunluk fonksiyonu ise aşağıdaki gibidir.

$$f(y) = \frac{1}{B(p,q)} \frac{(y-a)^{p-1}(b-y)^{q-1}}{(b-a)^{p+q-1}}, \quad p > 0, q > 0 \text{ ve } a < y < b.$$

$B(p, q)$ beta fonksiyonunu göstermektedir ve hesaplanması şu şekildedir.

$$B(p, q) = \int_0^1 t^{p-1}(1-t)^{q-1} dt$$

Parametrik dağılımlar, bazen verideki basıklığı, çarpıklığı ya da çok tepeli olma gibi durumları iyi temsil edemeyebilir. Bu durumda verinin istatistiksel dağılımı için parametrik olmayan yöntemler kullanılmaktadır. Kernel

tahmin edicisi, verinin dağılımı için sıkça kullanılan parametrik olmayan bir yöntemdir. Birbirinden bağımsız ve aynı dağılımlı $Y = (Y_1, \dots, Y_n)$ serisi için, Y 'nin Kernel tahmin edicisi aşağıdaki gibidir.

$$\tilde{f}(y) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{y-Y_i}{h}\right) \quad (5)$$

K , $\int K(y)dy = 1$ yani olasılık toplamının 1 olması koşulunu sağlamaktadır. Eşitlik 5'te, n , gözlem sayısını; h , düzeltme parametresi ya da bant genişliğini göstermektedir. Kernel tahmin edicisi, her bir gözlemdeki sıçramaların toplamı olarak ifade edilmektedir. Kernel fonksiyonu da, bu sıçramaların biçimini belirlemektedir (Silverman, 2018). Bu çalışmada K için Gaussian Kernel fonksiyonu kullanılmıştır. Gaussian Kernel fonksiyonu,

$$K(y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}$$

biçimindedir. Bant genişliği h için formül aşağıda verilmiştir (16).

$$h = 0.9An^{-\frac{1}{5}}$$

Bu eşitlik için $A = \min\left(\sigma, \frac{3.çeyreklik\ değeri}{1.34}\right)$ eşitliği yardımıyla bulunmaktadır.

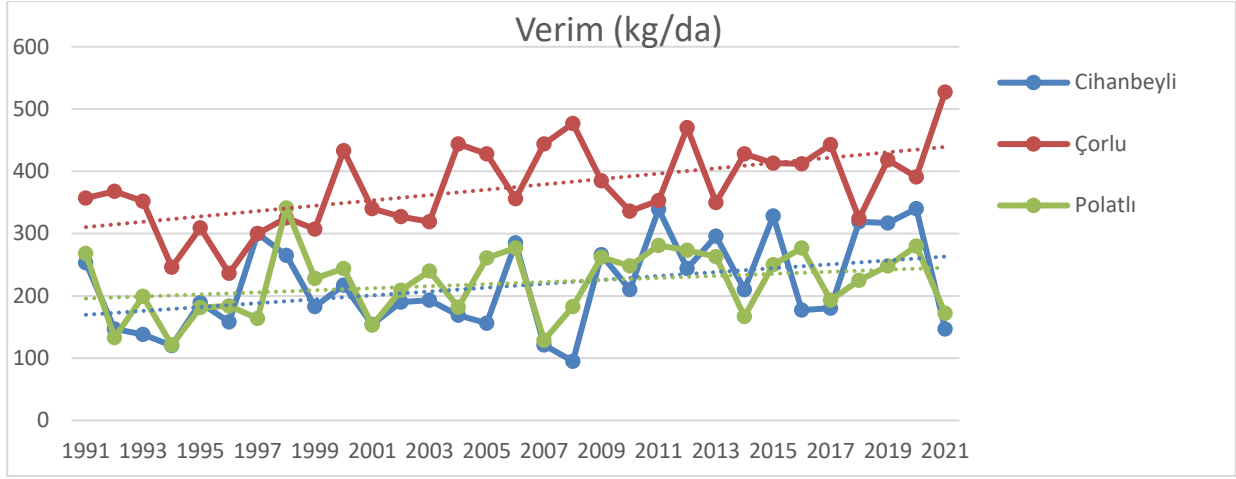
3. Bulgular ve Tartışmalar

Bu çalışma için Konya iline bağlı, Cihanbeyli; Tekirdağ iline bağlı, Çorlu ve Ankara iline bağlı, Polatlı ilçelerine ait 1991-2021 yıllarına ait buğday verim verisi kullanılmıştır. Bu ilçelerin seçilmesinin sebebi, kendi illeri için buğday üretimlerinin yüksek olmasıdır. Buğday verimine ait istatistiksel bilgiler Tablo 1'de gösterilmiştir.

Tablo 1. Yıllara göre ilçelere ait buğday verimi (kg/dekar) istatistikleri

İlçe	N	Ortalama	Standart Sapma	Çarpıklık	Basıklık	Min	Maks	Genişlik
Cihanbeyli	31	216,32	72,24	0,31	-1,12	95,00	340,00	245,00
Çorlu	31	374,77	67,55	0,07	-0,23	236,00	527,00	291,00
Polatlı	31	220,52	54,07	-0,08	-0,65	121,00	341,00	220,00

Tablo 1'e göre 31 yıllık buğday verilere için Çorlu ilçesine ait verim verisinin en yüksek ortalamaya sahip olduğu görülmektedir. Cihanbeyli ve Polatlı ilçelerine ilişkin ortalama verim değerleri ise birbirine yakın değerlerdir. Buğday verimi verilerinin trend içerip içermediğini incelemek amacıyla Eşitlik 1'de verilen doğrusal trend denklemi verilere uygulanmıştır. İlçeler için yıllar itibarıyla verim miktarları ve trend Şekil 1'de gösterilmiştir.



Kaynak : TÜİK, 2022

Şekil 1. İlçeler için yıllara göre buğday verimleri

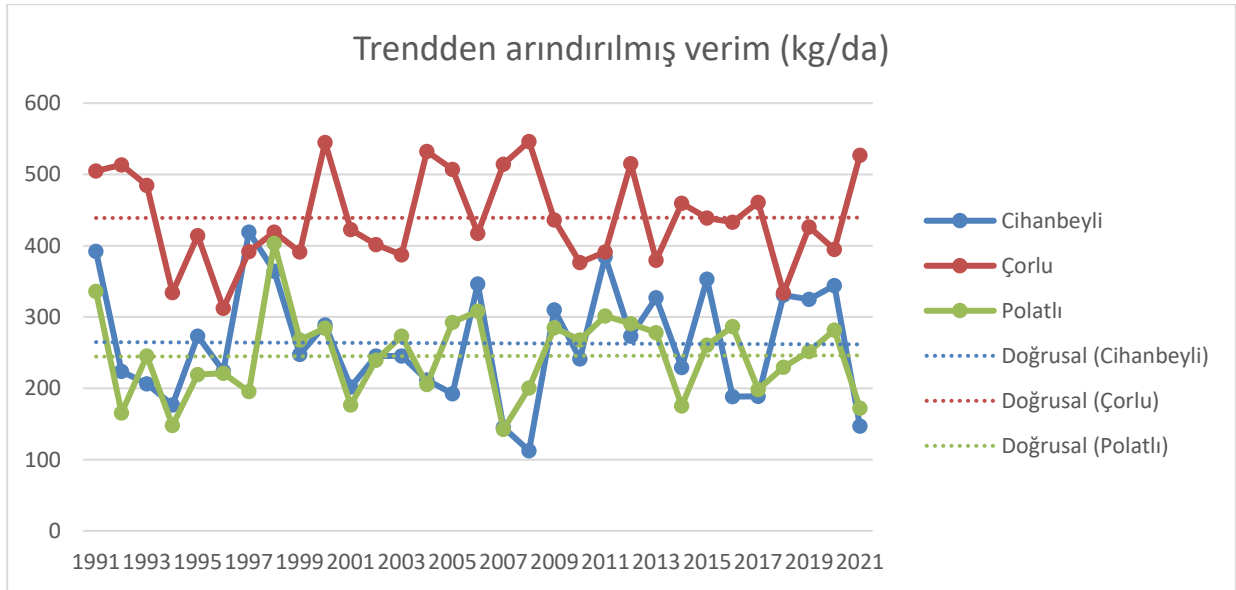
Tüm ilçeler için trend, Şekil 1’de kesikli çizgiler ile gösterilmiştir. Eşitlik 1 kullanılarak trend için elde edilen tahmin denklemleri aşağıda verilmiştir.

$$\hat{y}_t^{trend} = -6301,4 + 3,11t, \quad t = 1991, \dots, 2021 \quad (\text{Cihanbeyli})$$

$$\hat{y}_t^{trend} = -8235,66 + 4,29t, \quad t = 1991, \dots, 2021 \quad (\text{Çorlu})$$

$$\hat{y}_t^{trend} = -3094,24 + 1,65t, \quad t = 1991, \dots, 2021 \quad (\text{Polatlı})$$

Yukarıda elde edilen \hat{y}_t^{trend} değerleri Eşitlik 3’te yerine konulursa ilçeler için trendden arındırılmış verim (y_{trend}^0) değerleri bulunmaktadır. İlçelere göre trendden arındırılmış verimler Şekil 2’de verilmiştir.



Şekil 2. İlçelere göre trendden arındırılmış buğday verimleri

Şekil 2 incelendiğinde ilçe buğday verimlerindeki trendin ortadan kalktığı ve yatay seyreden bir doğru haline geldiği görülmektedir. Veriler trendden arındırıldıktan sonra R programı kullanılarak değişen varyanslılık sorunu için "ArchTest" testi yapılmıştır. Test sonuçları Tablo2'de verilmiştir.

Tablo 2. Değişen varyanslılık test sonuçları

	p test değeri
Cihanbeyli	0,3351*
Çorlu	0,1949*
Polatlı	0,3109*

$p * < 0,05$

Tablo 2'de trendden arındırılan veriler için değişen varyanslılık test sonuçlarına göre p test değerleri $0,05$ 'ten büyük olduğundan, verilerde değişen varyanslılık sorununun olmadığını %95 güven düzeyinde söyleyebiliriz ($H_0 = ARCH$ (otoregresif koşullu değişen varyans) etkisi yoktur).

Normal, Beta ve parametrik olmayan Gaussian Kernel tahmin edicisine göre ilçelere ait prim oranları Tablo 3'te gösterilmiştir. Veriler, trend içeren ve içermeyen veriler olmak üzere ayrı ayrı incelenip, prim oranları bulunmuştur. Böylece trendden arındırma işleminin prim oranlarının nasıl değiştirdiği de görülmek istenmiştir. Bütün ilçeler için trend içeren verilere ait prim oranlarının daha yüksek olduğu görülmüştür. Tarımsal teknolojinin artmasıyla birlikte buğday tohumu için yapılan modern ıslah çalışmaları yıllar itibarıyla buğday veriminde yukarı yönlü doğrusal bir trendin olması sonucunu doğurmaktadır. Çalışmada buğday verimi verisi için trendden arındırma işlemi, teknolojik gelişmelerin en yüksek temsil edildiği 2021 yılı seçilerek yapılmıştır. Dolayısıyla üç ilçe için de trendden arındırılan buğday verimleri, trend içeren verilere göre daha büyük olmaktadır. Trend içeren verilere ait buğday verimlerinin daha düşük olması hasat döneminde gerçekleşen buğday veriminin, Eşitlik 4'te verilen $c\bar{y}$ eşikdeğerinden düşük olması olasılığını artırmaktadır. Yani, Eşitlik 4'te verilen $c\bar{y}$ eşik değeri için trend içermeyen verilere ait eğrilerin altında kalan alan, trend içeren verilere göre daha küçük olmaktadır. Buğday verimine ait dağılım eğrisi için eşik değerden küçük olan alanın azalması, daha düşük risk anlamına gelmektedir. Bu sebeple, sigorta şirketi eşik değerinin altında gerçekleşecek verimler için teminat ödeyeceğinden, hasar olasılığının yüksek olması durumunda primlerin yüksek çıkması beklenen bir durumdur. Ayrıca trendden arındırma işlemi ile buğday verimindeki değişkenliğin azaltılması sonucunda, buğday verimi verileri için iklim değişikliğinin prim oranlarına etkisi de gözlemlenebilmektedir.

Tablo 3. İlçelere göre trend içeren ve trendden arındırılmış veriler için prim oranları

		Prim oranları (%)					
		trend içeren veri			trendden arındırılmış veri		
	Teminat oranı (%)	Normal	Beta	Gaussian Kernel	Normal	Beta	Gaussian Kernel
Cihanbeyli	70	4,47	5,42	4,95	3,49	3,51	4,13
	75	5,51	6,47	6,31	4,45	4,53	5,31
	80	6,70	7,62	7,85	5,59	5,70	6,68
	85	8,05	8,87	9,54	6,90	7,03	8,23
	90	9,55	10,22	11,35	8,39	8,53	9,94
Çorlu	70	0,47	0,41	0,69	0,16	0,31	0,17
	75	0,85	0,79	1,15	0,35	0,58	0,43
	80	1,44	1,39	1,81	0,73	1,03	0,90
	85	2,31	2,28	2,79	1,38	1,72	1,67
	90	3,52	3,52	4,14	2,40	2,73	2,86
Polatlı	70	1,75	1,76	2,44	1,67	1,23	2,05
	75	2,50	2,53	3,43	2,38	1,95	3,00
	80	3,44	3,51	4,62	3,31	2,92	4,17
	85	4,62	4,72	6,01	4,47	4,17	5,52
	90	6,04	6,15	7,57	5,89	5,68	7,05

Yıllara göre ortalama verimin en düşük olduğu ilçe Cihanbeyli için tüm yöntemler için prim oranları daha yüksek çıkmaktadır. Bu durum, düşük verim ortalamasına sahip bölgelerin gelir sigortası açısından daha riskli olduğunu yani yıllık hasat döneminde gerçekleşen verimin, eşik değeri altında kalması olasılığının yüksek olduğunu göstermektedir. Çorlu ilçesi için prim oranlarının diğer iki ilçeye göre düşük olması da yıllara göre verim ortalamasının yüksek olmasından kaynaklanmaktadır.

Tablo 3 incelendiğinde parametrik olmayan Kernel tahmin edicisine göre elde edilen prim oranlarının tüm ilçeler için parametrik yöntemlere göre yüksek olduğu görülmüştür. Parametrik olmayan yöntemlerin verideki çarpıklığı, çok tepeli olma gibi durumları iyi göstermesinden yani veriyi yumuşatmasından (smoothing) dolayı, verideki yoğunlukların kuyruklarına parametrik yöntemlere göre daha fazla kütle ekleyerek olasılığı artırmaktadır. Bu sebeple Kernel tahmin edicisine göre prim oranları daha yüksek çıkmaktadır.

4. Sonuç ve Öneriler

Bu çalışmada Cihanbeyli, Çorlu ve Polatlı ilçelerine ait 31 yıllık ortalama buğday verimleri kullanılarak ilçe bazlı veriler için verim sigortasına ilişkin trend içeren ve içermeyen veri olmak üzere ayrı ayrı prim oranları elde edilmiştir. Verilerin modellenmesi aşamasında tarımsal veriler için literatürde sıkça kullanılan parametrik dağılımlardan Normal, Beta ve parametrik olmayan yöntemlerden Kernel tahmin edicisi kullanılmıştır.

Trend içeren verilerin, trendden arındırılan verilere göre daha yüksek prim oranlarına sahip olduğu görülmüştür. Prim oranları, ortalama buğday veriminin en yüksek olduğu Çorlu ilçesi için en düşük, ortalama verimin en düşük olduğu ilçe olan Cihanbeyli ilçesi için en yüksek çıkmıştır.

Bu çalışmanın motivasyonu, Türkiye için yeni bir uygulama olan verim sigortası için ilçe bazlı veriler kullanılarak bilinen dağılımlar yardımıyla prim oranlarının belirlenmesi olduğundan, verideki çarpıklığı, basıklığı da içerecek diğer parametrik ve parametrik olmayan yöntemler de kullanılarak çalışma ileriye götürülebilir. Ayrıca tarımsal

ürünler için gerçekleştirilecek verimi tahmin etmek amacıyla, konumsal-mekansal etkilerin de gözlemlenebileceği modeller geliştirilerek bitkisel ürünler için daha etkin verim tahminleri yapılabilir.

Gelişmiş ülkeler için tarım, sağlık ve ekonomi gibi temel alanlarda verinin merkezde toplanması önemli bir yer tutmaktadır. Bireysel verilere ulaşımın kolay olduğu ülkeler, bu verilerden yola çıkarak ilgili alanlar için önemli kararlar alabilmektedirler. Türkiye gibi tarım ülkesi olan bir ülke için çiftçi bazlı verilerin sürekli olarak toplanması ve bu veriler ışığında politikalar geliştirmek hayati bir önem kazanmaktadır. Çiftçi bazlı verilerin kullanılması ile tersine seçim ve ahlaki tehlike gibi sigorta piyasasında başarısızlığa yol açan sebepler daha da azaltılarak etkili ve süreklilik kazanan bir tarım sigortası talebi yaratılabilir.

Teşekkür: Bu çalışmaya, önerileriyle ve değerlendirmeleriyle önemli katkılar sağlayan Prof. Dr. Ş.Kasırga Yıldırak'a teşekkürlerimi sunarım.

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Aspir Üretim Etkinliğinin Belirlenmesi: Trakya Bölgesi Örneği

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Özet

Türkiye’de uzun yıllardır bir bitkisel yağ açığı bulunmaktadır. Yağlı tohumlu bitkilerin verimlerinin artırılmasına yönelik çalışmaların yanı sıra zaman zaman alternatif yağ bitkilerinin de üretim desenine dahil edilmesi tartışılmaktadır. Alternatif yağ bitkilerinden biri olan aspir, %35’lik yağ oranına sahip olup Türkiye’de kurak iklimin hakim olduğu bölgelerde yetiştirilme potansiyelini korumaktadır. Çalışmanın amacı, Trakya Bölgesinde aspir üretimi yapan tarım işletmelerinin üretim etkinliklerinin belirlenmesidir. Etkinlik analizinde veri zarflama analizinden yararlanılmıştır. Çalışmada Trakya Bölgesinde aspir tarımının geliştirilmesine yönelik bir proje kapsamına dahil olan 47 üreticiden elde edilen üretim verileri kullanılmıştır. Trakya bölgesinin ortalama etkinlik katsayısı 0,532 olarak hesaplanmıştır. Çalışma sonucunda Trakya bölgesinde mevcut şartlarda aspir üretiminin yapılmasının uygun olmadığı sonucu ortaya koyulmuştur.

Anahtar Sözcükler: Etkinlik Analizi, Veri Zarflama Yöntemi, Teknik Etkinlik, Ölçek Etkinliği

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Determination of Safflower Production Efficiency: the Case of Trakya Region

Abstract

There has been a vegetable oil shortage in Turkey for many years. Besides to the studies to increase the yield of oilseeds, the inclusion of alternative oilseeds in the production pattern is discussed from time to time. Safflower, which is one of the alternative oilseeds, has an oil rate of 35% and maintains its potential to be grown in regions with arid climate in Turkey. The aim of the study is to determine the production efficiency of the agricultural enterprises producing safflower in the Trakya Region. Data envelopment analysis was used in the efficiency analysis. In the study, the production data obtained from 47 producers included in the scope of a project for the development of safflower agriculture in the Trakya Region were used. The average efficiency coefficient of the Trakya Region was calculated as 0.532. As a result of the study, it has been revealed that safflower production in the Trakya Region is not suitable under the current conditions.

Keywords: Efficiency Analysis, Data Envelopment Method, Technical Efficiency, Scale Efficiency

1. Giriş

Türkiye’de, bitkisel yağ talebinin karşılanması için başta ayçiçeği olmak üzere soya, pamuk, zeytin, yer fıstığı, mısır ve susam gibi yağ bitkileri kullanılmaktadır. 2020 yılı verilerine göre Türkiye’de 4,3 milyon ton yağlı tohum üretilmiştir. Bu miktar içerisinde 2 milyon ton üretim ve %47 oran ile ayçiçeği birinci sıradadır. 1,7 milyon ton üretim ve %40 oran ile çığit ikinci sırada yer almaktadır. Aspir ise 21 bin ton üretim ve %0,05 oran ile son sıralarda yer bulmaktadır (FAO, 2022). Türkiye’de yaklaşık 3 milyon ton bitkisel yağ talebi bulunmaktadır. Toplam bitkisel yağ talebinin 1,5 milyon tonu yurtiçi üretimden karşılanabilmekte geriye kalan kısmı ithalat yoluyla karşılanmaktadır.

Özellikleri itibariyle kullanım alanı geniş bir yağ bitkisi olan aspir, Türkiye’deki yağlı tohum ihtiyacı açığını kapatmada iddialı bir bitkidir. Aspir, %35’lik yağ oranına sahip olup Türkiye’de kurak iklimin hakim olduğu bölgelerde yetiştirilebilecek potansiyelde bir yağ bitkisidir.

Tarımsal üretimde etkinlik ölçümü üretimin sürdürülebilirliği açısından önem arz etmektedir. Türkiye’nin bitkisel yağ açığını kapatma potansiyeline sahip aspir üretiminin etkinliğinin ölçülmesi bu bağlamda önem taşımaktadır.

Tarımsal üretimde etkinlik analizinin kullanıldığı çok sayıda bilimsel çalışmaya rastlamak mümkündür. Shafiq ve Rehman (2000), Aktürk ve Kırıl (2002) pamuk, Dhungana ve ark. (2004) mısır, Parlakay (2011) yer fıstığı, Unakitan ve Lorcu (2011) kanola, Engindeniz ve Coşar (2013) domates, Canan (2014) çeltik, Hazneci (2015) şeker pancarı, Aydın ve Unakitan (2018) buğday ve ayçiçeği ürünlerinde teknik etkinlik analizinde veri zarflama yönteminden yararlanmışlardır.

Çalışmanın amacı, Trakya Bölgesinde aspir üretimi yapan tarımsal işletmelerin üretim etkinliklerinin belirlenmesidir. Veri zarflama analizi ile işletmelerde üretimin etkin sınırlar içinde yapılıp yapılmadığı belirlenmiştir. Çalışma sonucunda aspir üreten işletmelerde etkinsizliğin kaynağı belirlenerek üretim etkinliğinin artırılmasına yönelik çözüm önerileri sunulmuş ve aspir üretiminin yaygınlaşmasına yönelik politika önerilerine yer verilmiştir.

2. Materyal ve Yöntem

2.1. Materyal

Çalışmanın hedef kitlesini Trakya bölgesinde yer alan Edirne, Kırklareli ve Tekirdağ illerindeki tarım işletmeleri oluşturması hedeflenmiş, Trakya bölgesinde yıllar bazında ÇKS kayıtları incelendiğinde sadece 2014 yılı ÇKS kayıtlarında sayısal yeterli sayılabilecek aspir üretimi yapan 70 üretici tespit edilmiştir. Ancak saha çalışması aşamasında Tekirdağ ve Edirne illerinde 47 üreticinin aspir ürettiği kalan 23 çiftçinin üretim aşamasında değişik

sebeplerden üretimden vazgeçtiği belirlenmiştir. Üretici sayısının sınırlı olması nedeniyle çalışmada örnekleme yapılmayıp tam sayım yoluyla veri toplanmıştır.

2.2. Yöntem

Çalışmada, işletme düzeyinde etkinlik ölçümleri veri zarflama yöntemiyle (VZA) yapılmıştır. VZA ile tek çıktılı üretim yerine çok çıktının bulunduğu üretim ortamlarında etkinlik ölçümü kolaylıkla gerçekleştirilebilmektedir (Yolalan, 1993). Üretim birimlerinin etkinliklerinin ölçülmesinde kullanılan başlıca metotlar parametrik ve non-parametrik metotlar olmak üzere iki gruba ayrılmaktadır. Veri Zarflama Analizi non-parametrik bir yöntemdir ve karar verme birimlerinin teknik etkinliğini hesaplamaktadır. Karar birimi "k" için teknik etkinlik; verilen bir girdi seviyesi için çıktılarının maksimize edilebilmesini sağlamakla birlikte verilen bir çıktı seviyesi için girdileri minimize edilebilmesini sağlamaktadır. Her karar alma birimindeki etkinsizlik miktarı ve kaynakları bu yöntem ile tanımlanabilir. VZA, etkin olmayan birimlerde ne kadarlık bir azaltma ya da çıktı miktarını artırma gerektiğine ilişkin olarak yol gösterici bilgi verebilmektedir (Gülcü ve ark., 2004).

VZA'nın en büyük avantajlarından birisi birden fazla girdisi ve çıktısı olan karar verme birimlerinin etkinliklerinin hesaplanabilmesidir. İncelenen karar birimlerinin ortalama etkinliğe sahip birimlerle değil tam etkin ya da etkin sınırdaki yer alan karar verme birimleri ile karşılaştırılması da avantaj olarak nitelendirilebilecek bir diğer özelliktir (Coelli vd., 1998).

İlk VZA modeli Charnes, Cooper ve Rhodes (1978) tarafından ortaya atılmış olup yazar isimlerine göre CCR olarak anılmaktadır. Bu model ölçeğe göre sabit getiri varsayımına dayalıdır. Banker, Charnes ve Cooper (1984), ölçeğe sabit getiri yaklaşımı (CCR), sadece bütün karar verme birimlerinin optimal ölçekte çalıştığı durumlarda geçerli olduğu için, ölçeğe göre sabit getiri varsayımına dayalı VZA modelini ölçeğe göre değişken getiriyi dikkate alarak BCC olarak anılan yaklaşımı geliştirmişlerdir. Üretim birimlerinin tümü optimal ölçekte faaliyette bulunmadıkları takdirde, ölçeğe göre sabit getiri tanımlamasının kullanımı, ölçek etkinlikleri ile karışmış bir teknik etkinlik ölçümüyle sonuçlanmaktadır. Bu yüzden ölçeğe göre değişken getiri tanımlamasının kullanımı, ölçek etkinliği etkilerinden arındırılmış bir teknik etkinlik hesaplanmasına olanak sağlamaktadır.

Eğer belirli bir üretim birimi için ölçeğe göre sabit getiri ve ölçeğe göre değişken getiri teknik etkinlik değerleri birbirinden farklı ise, bu durum üretim biriminin ölçek etkinsizliğine sahip olduğunu göstermektedir. Buna göre ölçek etkinliği aşağıdaki şekilde açıklanabilir (Eşitlik 1) (Zaim, 1999);

$$\text{Ölçek etkinliği} = \text{Toplam teknik etkinlik} / \text{Saf teknik etkinlik} \quad (1)$$

Ölçeğe sabit getirili modellerde, girdi miktarında meydana gelebilecek bir artış, çıktı miktarında da aynı oranda olmaktadır, ölçeğe değişken getirili modellerde ise, girdi miktarındaki bir artış, çıktı miktarında farklı oranlarda olmaktadır.

Girdiye yönelik ölçümlerde amaç, girdi miktarlarının, üretilen çıktı miktarında değişiklik yapmadan oransal olarak ne kadar azaltılabileceğinin belirlenmesidir. Çıktıya yönelik ölçümlerde amaç, girdi miktarlarında değişiklik yapmadan çıktı miktarının ne kadar artırılabilirliğinin belirlenmesidir. Çıktı odaklı model, girdi odaklı modelin tam tersidir. Girdi miktarlarının sabit tutularak çıktı miktarlarında ortaya çıkabilecek değişimlerin incelenmesi olarak tanımlanır.

Ölçek etkinliği veya etkinsizliği, ölçeğe göre sabit getiri ve ölçeğe göre değişken getiri etkin sınırı arasındaki uzaklık olarak ifade edilir.

Bir üretim faaliyetinin optimum ölçekte üretim yapma başarısı ölçek etkinliği olarak tanımlanmaktadır. Bir işletmenin elinde bulundurduğu girdi bileşimini optimum biçimde kullanarak mümkün olan en çok çıktıyı üretmedeki başarısı teknik etkinlik olarak tanımlanmaktadır.

Çalışmada, veri zarflama analizi girdiye yönelik ve değişken getiri varsayımı altında yapılmıştır. Aspir üretim miktarı (kg) çıktı olarak kullanılırken, üretim alanı (da), tohumluk (kg), azot (kg), potasyum (kg), işgücü (sa) ve dizel yakıt (lt) girdiler olarak belirlenmiştir.

3. Araştırma Bulguları

Çalışma Trakya Bölgesinde faaliyet gösteren aspir üreticilerinden elde edilen veriler ile yapılmıştır. Ortalama aspir verimi, Tekirdağ ilinde 74,11 kg/da, Edirne ilinde ise 39,17 kg/da'dır. Ortalama verimin bu kadar düşük olmasının nedeni üretim sezonunda meydana gelen aşırı yağışların olumsuz etkileri ve bitkinin kritik gelişim evrelerinde ekili alanlarda meydana gelen göllenmelerden kaynaklanan verim kayıplarıdır (İldız ve Unakıtan, 2022). İllere göre aspir verimi istatistiki olarak karşılaştırıldığında “İller arasında verim farklı bulunmamaktadır” boş hipotezi reddedilmektedir ($p<0.05$).

Çalışmada uygulanan veri zarflama analizi sonucunda teknik etkinlik, saf teknik etkinlik ve ölçek etkinliği katsayıları elde edilmiştir. Tablo 1’de görüldüğü üzere aspir üretiminde saf teknik etkinlik skorları 0,13 ile 1,00 arasında değişim göstermektedir. Saf teknik etkinlik katsayısı 0,615 hesaplanmıştır. Buna göre işletmeler çıktılarında herhangi bir azalma olmaksızın girdilerini %38 oranında azaltabileceklerdir.

Ölçek etkinliği sonuçları incelendiğinde katsayıların 0,39 ile 1,00 arasında değiştiği görülmektedir. Ortalama ölçek etkinliği 0,899 hesaplanmıştır. Ölçek etkinliğinin birden küçük olması ölçek etkinsizliğinin varlığına işaret etmektedir.

Tablo 1. Trakya bölgesinde etkinlik katsayıları

	Ortalama	Standart Sapma	Minimum	Maksimum
Teknik Etkinlik	0,547	0,265	0,12	1,00
Saf Teknik Et.	0,615	0,280	0,13	1,00
Ölçek Etkinliği	0,899	0,142	0,39	1,00

İllere göre etkinlik katsayıları incelendiğinde Tekirdağ ilindeki teknik etkinlik ve saf teknik etkinlik katsayılarının görece olarak Edirne ilindeki katsayılara göre yüksek olduğu görülmektedir. Saf teknik etkinlik katsayılarına göre açıklanacak olursa, Tekirdağ ilinde saf teknik etkinlik katsayısı 0,68 hesaplanmış olup (Tablo 2) işletmelerin aynı üretim düzeylerine %32 daha az girdi kullanarak ulaşabilecekleri görülmektedir. Edirne ilinde ise işletmeler aynı üretim düzeylerine %64 daha az girdi kullanarak ulaşabileceklerdir. Görüldüğü üzere Edirne ilinde Tekirdağ iline göre çok yüksek bir etkisizlik söz konusudur. İllerin teknik etkinlik katsayıları arasında yapılan istatistiksel karşılaştırmada öncelikle Kolmogorov-Smirnov normal dağılım testi yapılmış ve skorların normal dağılım göstermediği anlaşılmıştır ($p<0,05$). Sonrasında non-parametrik karşılaştırma testlerinden Mann-Whitney U testi uygulanmış Tekirdağ ve Edirne illeri için teknik etkinlik ($p<0,01$) ve saf teknik etkinlik ($p<0,01$) katsayıları arasında anlamlı bir fark olduğu, ölçek etkinliği katsayıları arasında ise ($p=0,788$) anlamlı bir fark olmadığı sonucuna varılmıştır.

Tablo 2. İllere göre etkinlik katsayıları

	Tekirdağ			Edirne		
	Ortalama	Minimum	Maksimum	Ortalama	Minimum	Maksimum
Teknik Etkinlik	0,607	0,12	1,00	0,322	0,22	0,56
Saf Teknik Et.	0,682	0,13	1,00	0,367	0,24	0,59
Ölçek Etkinliği	0,899	0,39	1,00	0,900	0,60	1,00

Tablo 3’te saf teknik etkinlik katsayılarının dağılımları ayrıntılı olarak verilmektedir. Tekirdağ ilinde etkin işletmelerin oranı %35 iken etkin olmayan işletmelerin oranı %65’tir. Edirne ilinde etkin işletme bulunmamaktadır. Edirne ilinde işletmelerin tümünün saf teknik etkinlik katsayısı 0,90’ın altındadır.

Tablo 3. İllere göre saf teknik etkinlik katsayılarının dağılımı

	Tekirdağ		Edirne	
	Sayı	%	Sayı	%
Etkin ($0.90 \leq TE \leq 1$)	13	35,13	0	0,00
Etkin değil ($TE \leq 0.899$)	24	64,87	10	100,00
Toplam	37	100,00	10	100,00

Tekirdağ ilinde aspir üreten işletmelerin %62'si ölçek etkinliğine sahip iken Edirne ilinde ölçek etkinliğine sahip işletmelerin oranı %80'dir. (Tablo 4.)

Tablo 4. İllere göre ölçek etkinliği katsayılarının dağılımı

	Tekirdağ		Edirne	
	Sayı	%	Sayı	%
Etkin ($0.90 \leq TE \leq 1$)	23	62,16	8	80,00
Etkin değil ($TE \leq 0.899$)	14	37,84	2	20,00
Toplam	37	100,00	10	100,00

Bir karar biriminin teknik etkinliği korunmak şartıyla, ölçeği büyütüldüğü zaman verimliliğinin artacağı söylenebilir. Bu durum ölçeğe göre artan getiri olarak ifade edilmektedir. Bir karar biriminin teknik etkinliğini korunarak ölçeği küçültüldüğü zaman verimliliğinde artış gözlenecektir ve ölçeğe göre azalan getiri olarak ifade edilmektedir.

İşletmelerin ölçeğe getiri durumları incelendiğinde Tekirdağ ilindeki işletmelerin %70'i ölçeğe artan getiriye sahip iken Edirne ilindeki işletmelerin % 80'i ölçeğe artan getiriye sahiptir. Buna karşılık Edirne'deki işletmelerin %20'si ölçeğe azalan getiriye sahiptir (Tablo 5).

Tablo 5. İllerin ölçeğe göre getiri durumları

	Tekirdağ		Edirne	
	Sayı	%	Sayı	%
Ölçeğe artan getiri	26	70,27	8	80,00
Ölçeğe sabit getiri	9	24,32	0	0,00
Ölçeğe azalan getiri	2	5,41	2	20,00
Toplam	37	100,00	10	100,00

Tablo 6 'da görüldüğü üzere işletmelerin saf teknik etkinlik katsayılarına göre girdi kullanım miktarları ayrıntılı olarak verilmektedir. Etkin işletmelerin girdi kullanım miktarları etkin olmayan işletmelere göre daha düşüktür. Bunun yanı sıra etkin işletmelerin ortalama verimleri de daha yüksektir.

Tablo 6. İşletmelerin etkinlik durumlarına göre girdi kullanımları

	İşgücü (sa/da)	Motorin (lt/da)	N (kg/da)	P (kg/da)	Tohum (kg/da)	Verim (kg/da)
Etkin ($0.90 \leq TE \leq 1$)	2,39	7,18	4,82	3,76	3,50	96,11
Etkin değil ($TE \leq 0.899$)	2,88	7,55	5,44	4,03	3,95	55,41
Tüm İşletmeler	2,75	7,45	5,27	3,95	3,82	66,67

4. Tartışma ve Sonuç

Bu çalışmada Trakya Bölgesinde aspir üretiminin etkinlik analizi yapılmış ve üretimde ortaya çıkan eksiklikler konusunda öneriler sunulmaya çalışılmıştır. Etkinliğin ölçülebilmesi için veri zarflama analizinden faydalanılmıştır.

İşletmelerin etkinlik katsayıları incelendiğinde, Tekirdağ ilinde faaliyet gösteren işletmelerin etkinlik katsayıları ortalaması 0,595 iken Edirne ili için 0,297 olarak hesaplanmıştır. Trakya bölgesinin ortalama etkinlik katsayısı ise 0,532 olduğu görülmektedir. Edirne ilindeki ortaya çıkan katsayının bu denli düşük olmasının sebebi, elde edilen verimlerin düşüklüğü şeklinde açıklanabilmektedir. Etkinlik açısından yapılacak değerlendirme de bu durum, işletmelerin çıktı miktarını korumak şartıyla girdi miktarlarında ortalama %47'lik bir azaltma sağladıklarında tam etkinliğe ulaşabilecekleri anlamına gelmektedir.

Araştırmada veri zarflama analizi, girdiye yönelik ve değişen getiri varsayımı altında yapılmıştır. İşletmelerin teknik olarak etkin çalışıp çalışmadıkları saf teknik etkinlik ve ölçek etkinliği ile ölçülmüştür. Yapılan analiz sonucunda teknik etkinlik, saf teknik etkinlik ve ölçek etkinliği katsayıları elde edilmiştir. Üretimde saf teknik etkinlik katsayısı 0,615 olarak belirlenmiştir. Bu sonuca göre işletmeler üretimde elde ettikleri çıktılarında herhangi bir azalma olmaksızın girdilerini %38 oranında azaltabilecekleri sonucuna varılmaktadır.

Ölçek etkinliği incelendiğinde katsayıların 0,39 ile 1,00 arasında değiştiği görülmektedir. Ortalama ölçek etkinliği 0,899 olarak hesaplanmıştır. Ölçek etkinliğinin birden küçük olması ölçek etkinsizliğinin olduğu ile ilgili bir durumun varlığını ortaya koymaktadır.

İllere göre etkinlik katsayıları incelendiğinde; Edirne ilinde faaliyet gösteren işletmelerde, Tekirdağ ilinde faaliyet gösteren işletmelere nazaran çok daha yüksek bir etkinsizlik olduğu görülmektedir. Araştırmada, işletmelerin ölçeğe getiri durumları incelendiğinde Tekirdağ ilindeki işletmelerin %70'i ölçeğe artan getiriye sahip iken Edirne ilindeki işletmelerin % 80'i ölçeğe artan getiriye sahiptir. Buna karşılık Edirne'deki işletmelerin %20'si ölçeğe azalan getiriye sahiptir.

Araştırma sonuçlarına göre; mevcut üretimin her iki ilde de teknik olarak etkin olmadığı, azot girdisi dışında diğer girdilerin arttırılması durumunda üretimde artış olabileceği anlaşılmaktadır. Ancak saha çalışmalarından elde edilen bulgular dikkate alındığında Trakya bölgesinde mevcut şartlarda aspir üretiminin yapılmasının uygun olmadığı sonucu ortaya konulmuştur.

Aspir bitkisinin Trakya bölgesinde mevcut şartlarda belirlenen sorunlar ve sebepler çerçevesinde yetiştiriciliğin yapılabilmesi ve yaygınlaşabilmesi için köklü çözümlere ihtiyaç duyulmaktadır. Yağ kalitesi ve kullanım alanları açısından önemli bir bitki olan aspir, Trakya bölgesi ürün deseninde münavebeye girmesi ve yağ açığına alternatif bir bitki olması açısından önemli bir bitkidir. Bu sebep ile bitkinin bölgeye kazandırılması amacıyla uzun vadeli planlar yapılmalıdır. Bitkinin bölgeye adaptasyonu, bölgeye uygun çeşitlerin belirlenmesi, etkinliğin artırılması için üretim aşamasındaki optimum girdilerin belirlenmesi, farklı lokasyonlarda denemelerin yapılması, çiftçi bazında demonstrasyonların kurulması, üretici birliklerin bu konuda devreye girmesi bu bağlamda ilgili kurumlar ve birlikler vasıtasıyla uzun vadeli eğitim faaliyetlerinin yapılması, pazarlama sorunun aşılabilmesi açısından aspir yağı üretimin teşvik edilmesi ile aspir bitkisi, uzun vade de Trakya bölgesinde kendine önemli bir yer bulabilecektir.

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